# Data Integration and Machine Learning: A Natural Synergy

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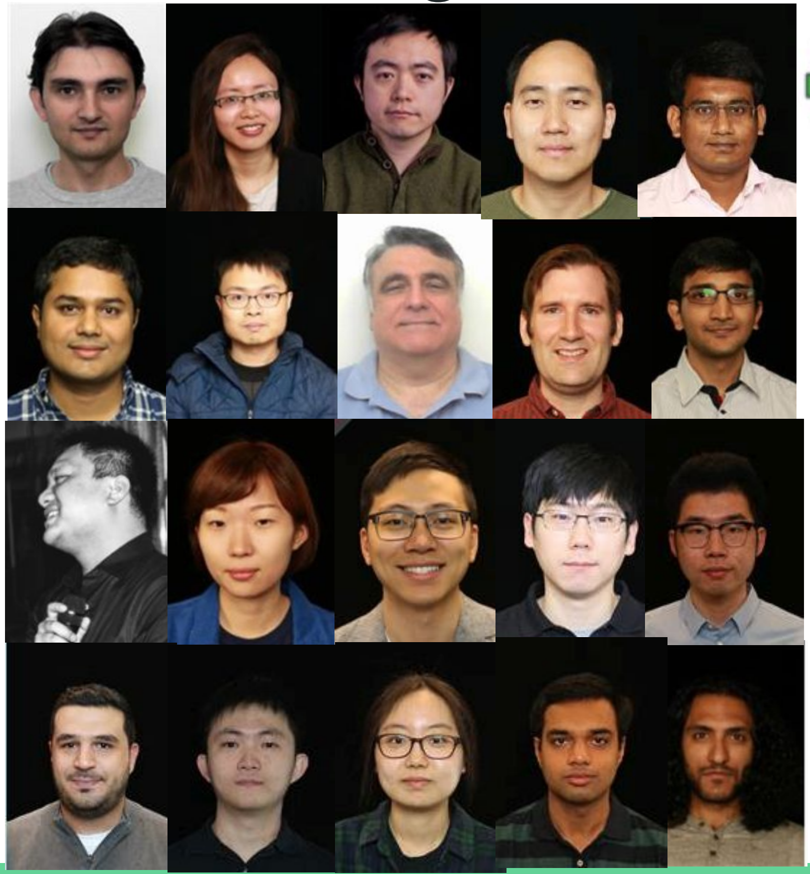
http://dataintegration.ai

# Acknowledgement



product graph

snorkel

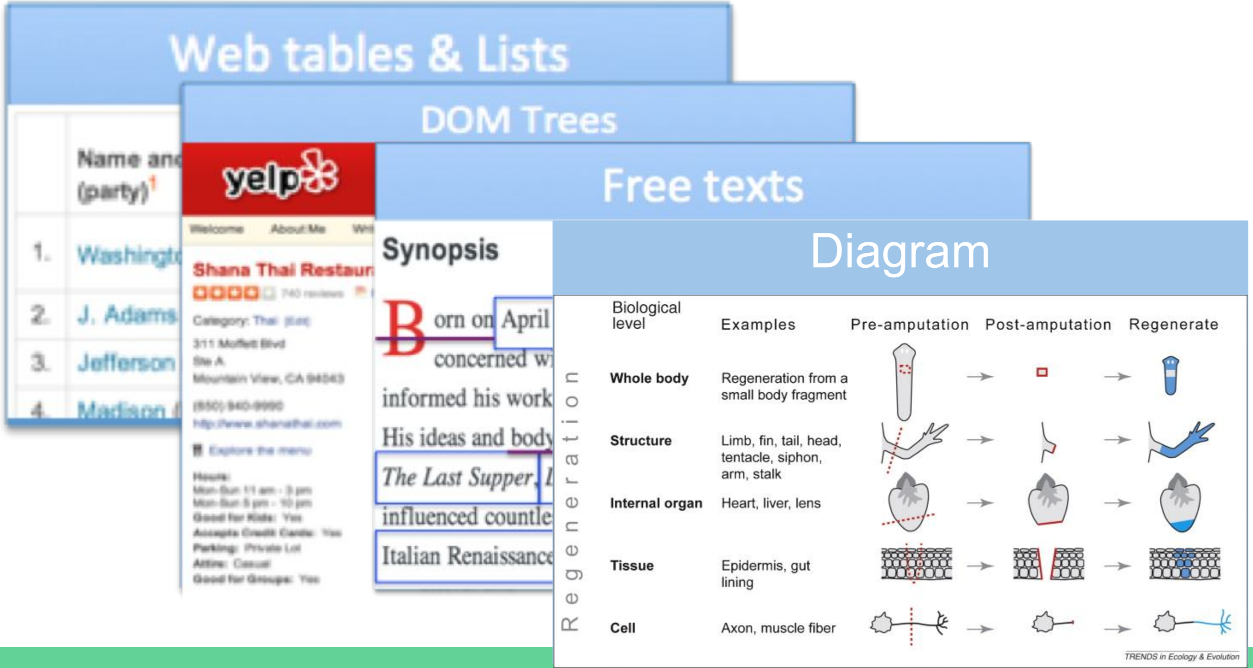
# What is Data Integration?

- **Data integration**: to provide unified access to data residing in multiple, autonomous data sources
    - **Data warehouse**: create a single store (materialized view) of data from different sources offline. Multi-billion dollar business.
    - **Virtual integration**: support query over a mediated schema by applying online query reformulation. E.g., Kayak.com.

- In the RDF world: different names for similar concepts
    - **Knowledge graph** is equivalent to a data warehouse. Has been widely used in Search and Voice
    - **Linked data** is equivalent to virtual integration

# Why is Data Integration Hard?

- Heterogeneity everywhere
  - Different data formats




**Data Extraction**

↓

Schema Alignment

↓

Entity Linkage

↓

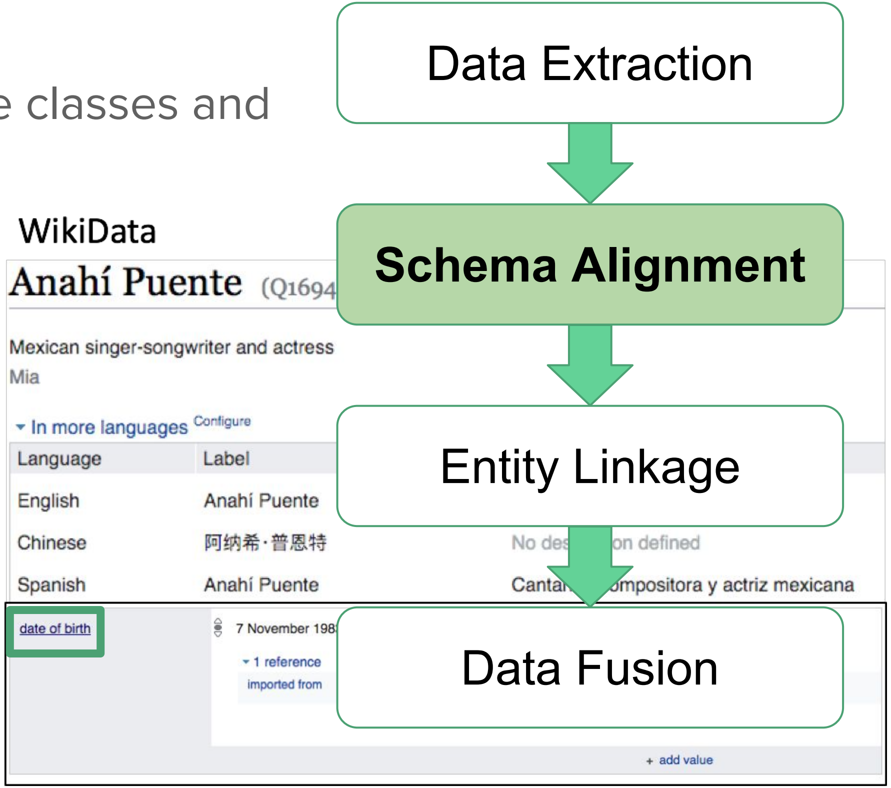
Data Fusion

# Why is Data Integration Hard?

- Heterogeneity everywhere
  - Different ways to express the same classes and attributes

IMDB


WikiData

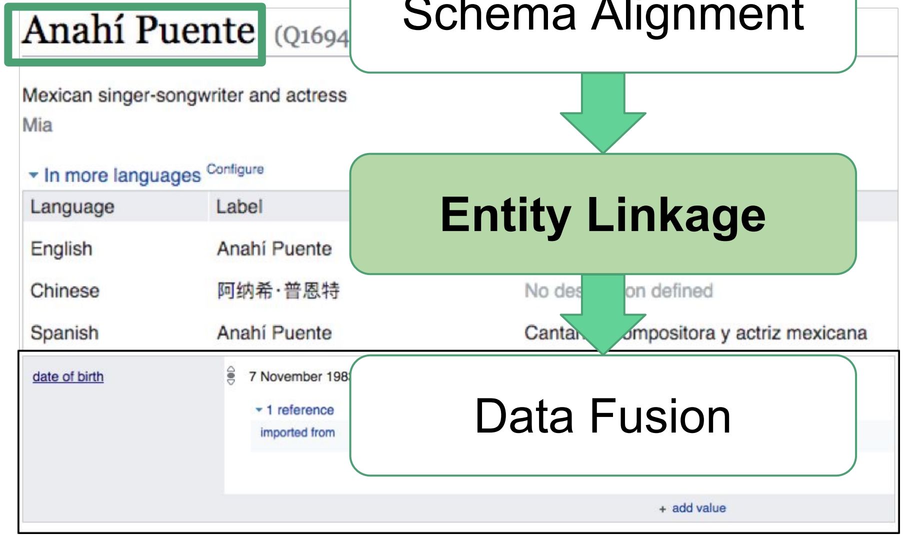


# Why is Data Integration Hard?

- Heterogeneity everywhere
    - Different references to the same entity

IMDB


WikiData




Data Extraction

↓

Schema Alignment

↓

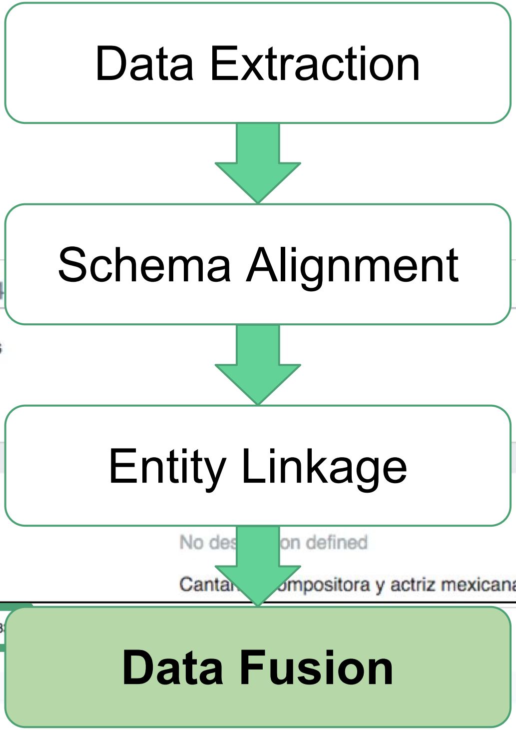
**Entity Linkage**

↓

Data Fusion

# Why is Data Integration Hard?

- Heterogeneity everywhere
  - Conflicting values

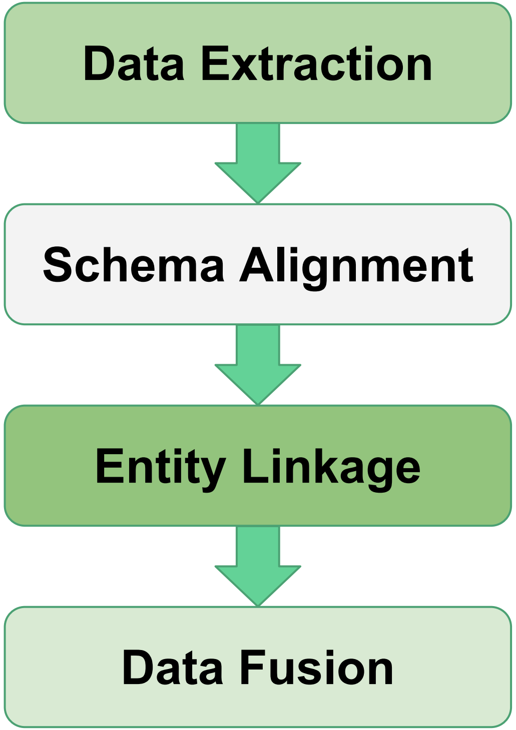



IMDB


WikiData

# Importance from a Practitioner's Point of View

- Entity linkage is indispensable whenever integrating data from different sources
- Data extraction is important for integrating non-relational data
- Data fusion is necessary in presence of erroneous data
- Schema alignment is helpful when integrating relational data, but not affordable for manual work if we integrate many sources



# What is Machine Learning?

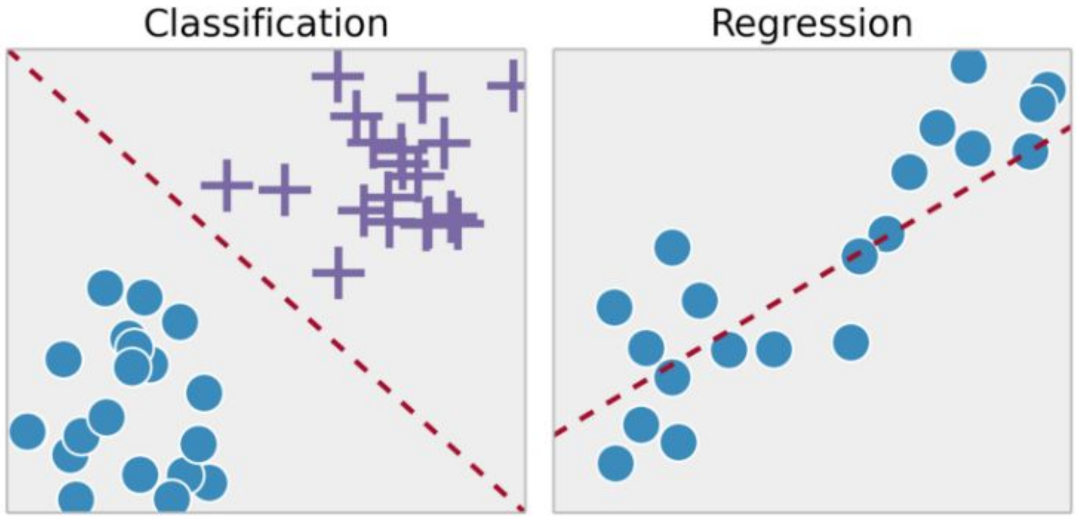
- **Machine learning:** teach computers to ***learn*** with data, not by programming

- **More Formal definition**
  A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, **improves with experience E**.

  -- Tom Mitchell

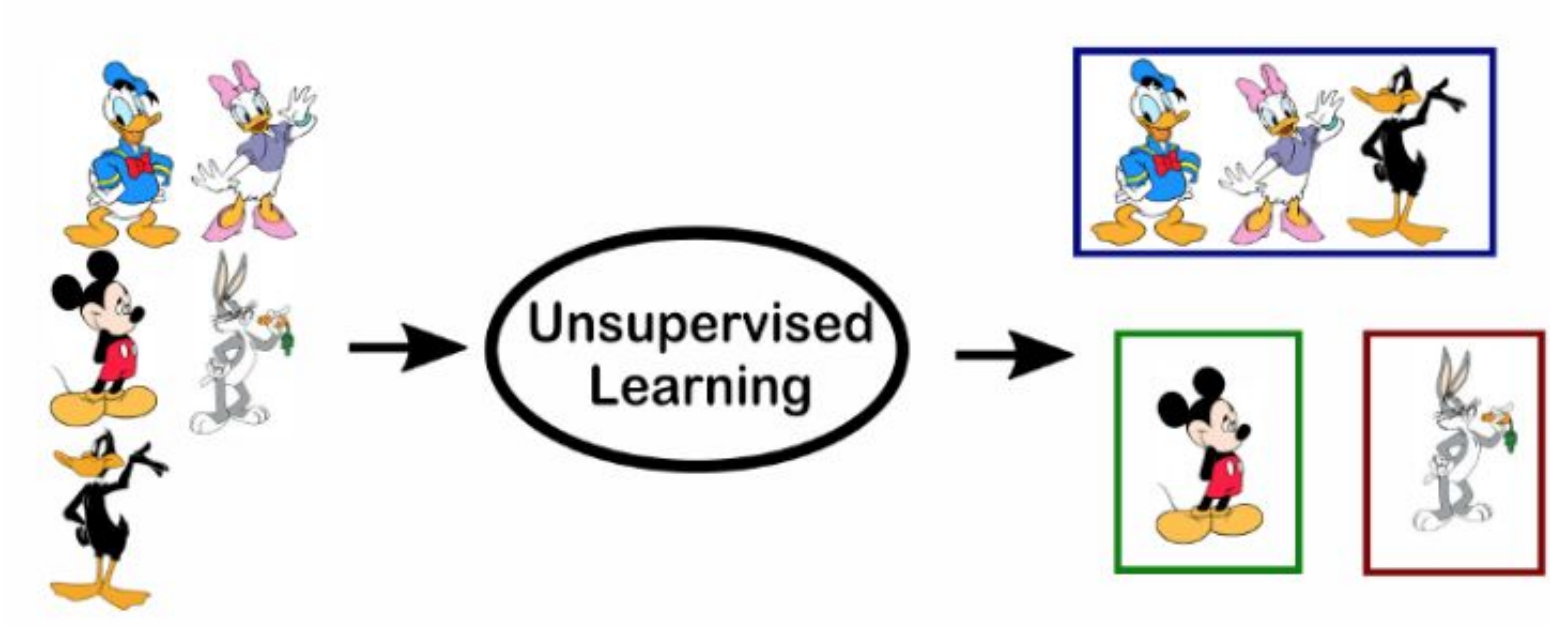
# Two Main Types of Machine Learning

- Supervised learning: learn by examples



# Two Main Types of Machine Learning

- Unsupervised learning: find structure w/o examples

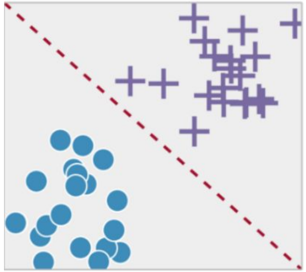
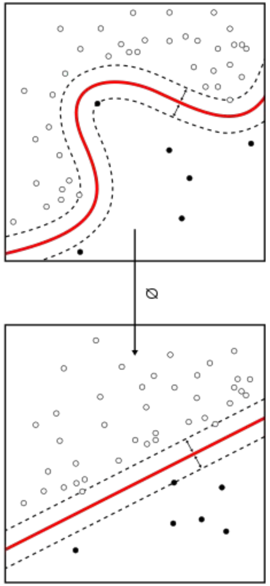
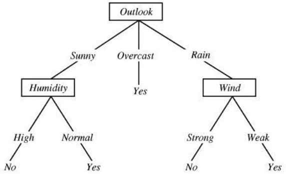
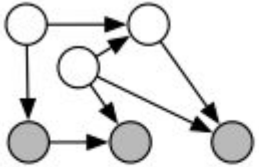
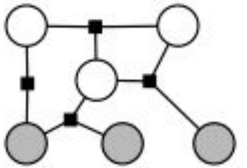
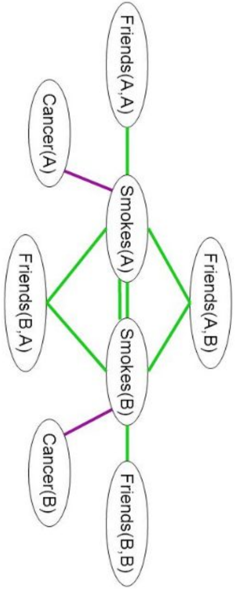
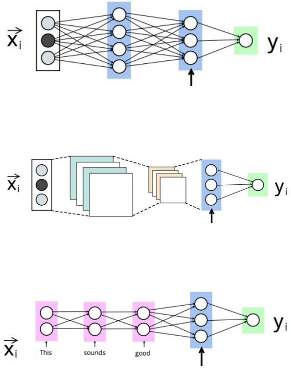


# Two Main Types of Machine Learning

- Supervised learning: learn by examples
- Unsupervised learning: find structure w/o examples

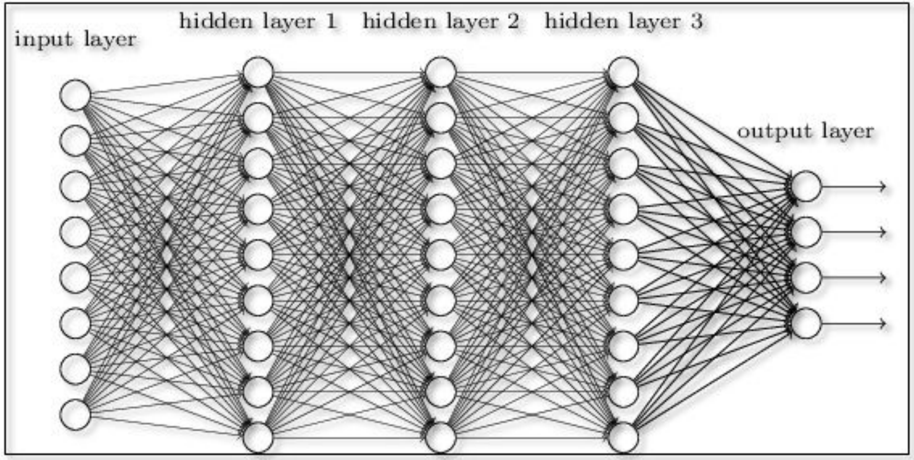
| | Supervised Learning | Unsupervised Learning |
|---|---|---|
| Discrete | classification or categorization | clustering |
| Continuous | regression | dimensionality reduction |

# Techniques for Supervised ML

| Hyperplanes | Kernel | Tree-based | Graphical Mdl | Logic Prog | Neural Netw |
|---|---|---|---|---|---|
| Linear/Logistic regression | SVM | Decision tree, Random forest | Bayes net, CRF | Pr soft logic, Markov logic net | ANN, CNN, RNN |
|  |   |   |   |   |   |

# Colin’s 7 minute intro to bidirectional LSTMs

# Everyone loves neural networks

- They have the word “neural” in them
- They have the word “network” in them
- You can draw fancy diagrams
- 

# Everyone loves neural networks

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- This thing:

# Everyone loves neural networks

- They have the word “neural” in them
- They have the word “network” in them
- You can draw fancy diagrams
- This thing:

- They are good at modeling high-dimensional non-linear functions and building sophisticated representations of complex sensory data

# What’s a neural network?

x

Input vector

# What’s a neural network?

$$Wx$$

Weight matrix

# What’s a neural network?

$$\sigma(Wx)$$

Non-linear function

e.g. sigmoid

# What's a neural network?

$$h = \sigma(Wx)$$

Hidden layer unit

# What's a neural network?

$$h = \sigma(Wx)$$

$$y = f(h)$$

Differentiable function

e.g. softmax

# Let’s use neural networks for language!

Classify sentences!

Tag parts of speech!

Find entity names!

Extract relations!

# Let’s use neural networks for language!

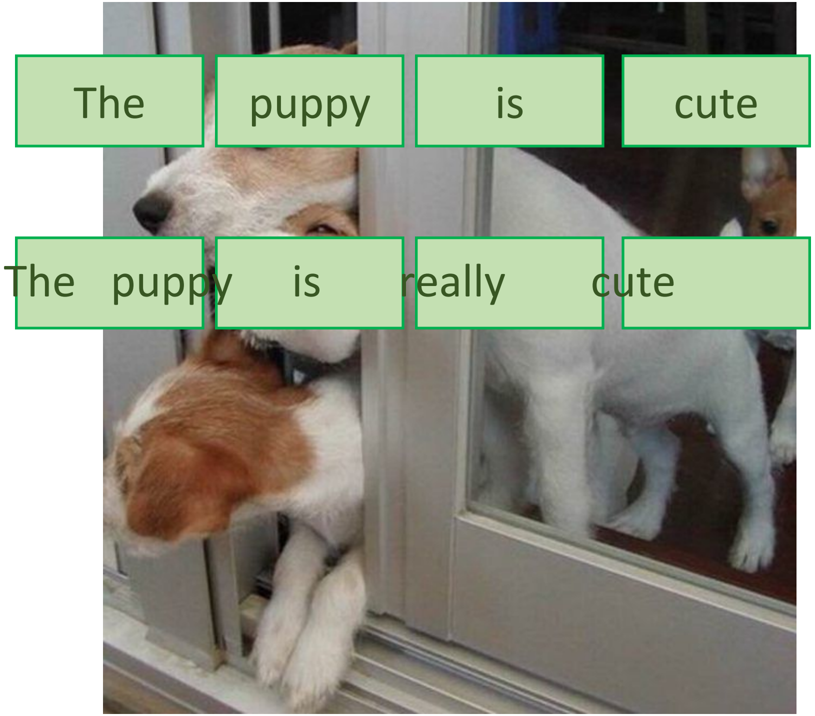
PROBLEM:

- Fixed # of weights
- Fixed # of features
- Fixed size of input

The puppy is cute.

The puppy is really cute.

Seriously, did you see this puppy, look how cute it is!



MR. WILLIAM

# SHAKESPEARES

## COMEDIES, HISTORIES, & TRAGEDIES.

Publiſhed according to the True Originall Copies.


*LONDON*

Printed by Iſaac Iaggard, and Ed. Blount. 1623.

# ☹

- Sentence classification
  - Sentences have variable length!
- Word tagging
  - Fixed-width window around word misses full context

# What's a neural network?

$$\cancel{h = \sigma(Wx)}$$

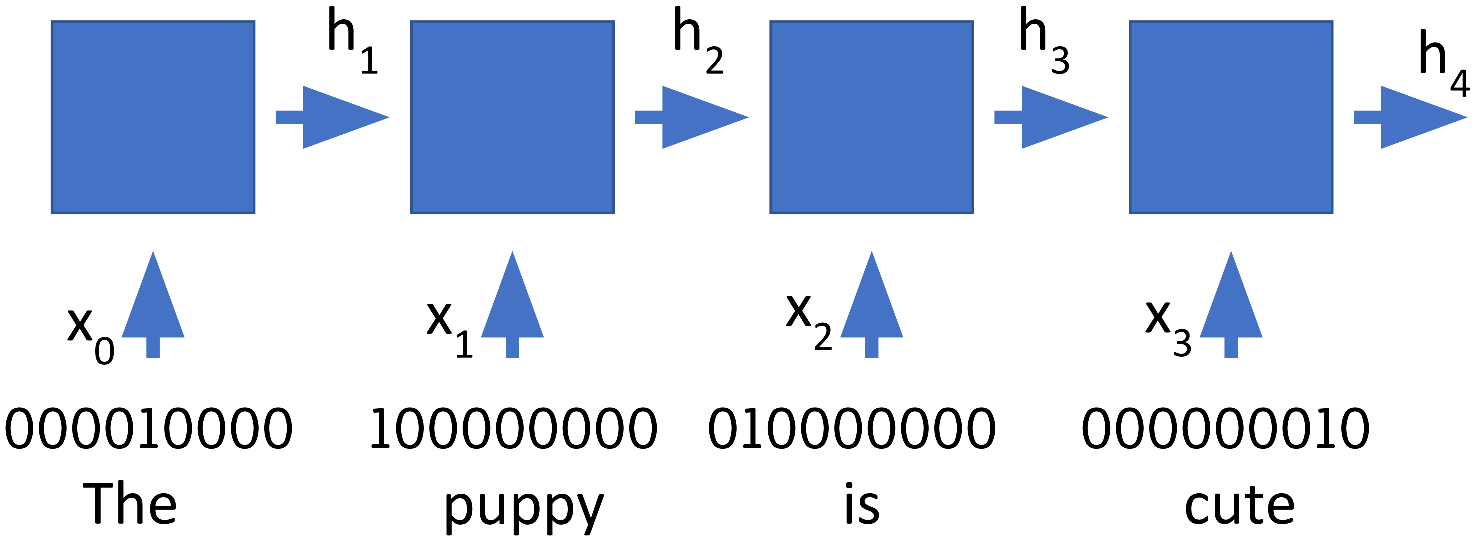
# What's a recurrent neural network?

$$\cancel{h = \sigma(Wx)}$$

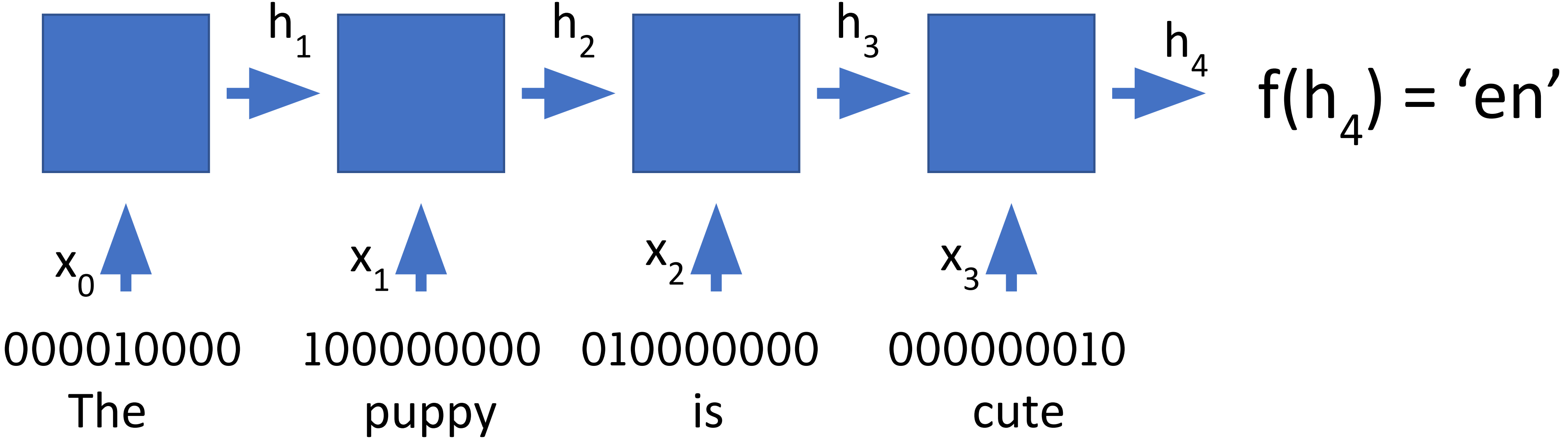
# What's a recurrent neural network?

$$\cancel{h = \sigma(Wx)}$$

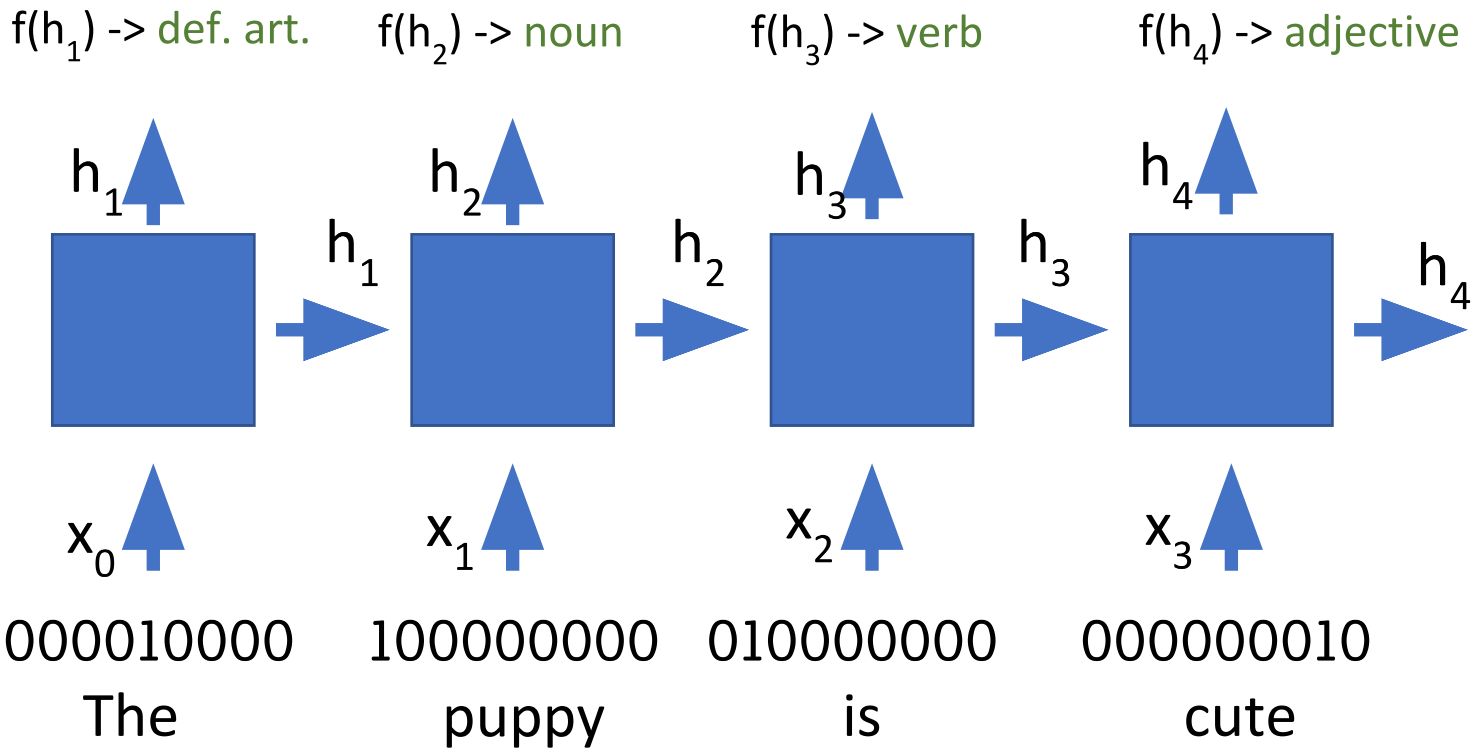
$$h_t = \sigma(Wx_t + Uh_{t-1})$$



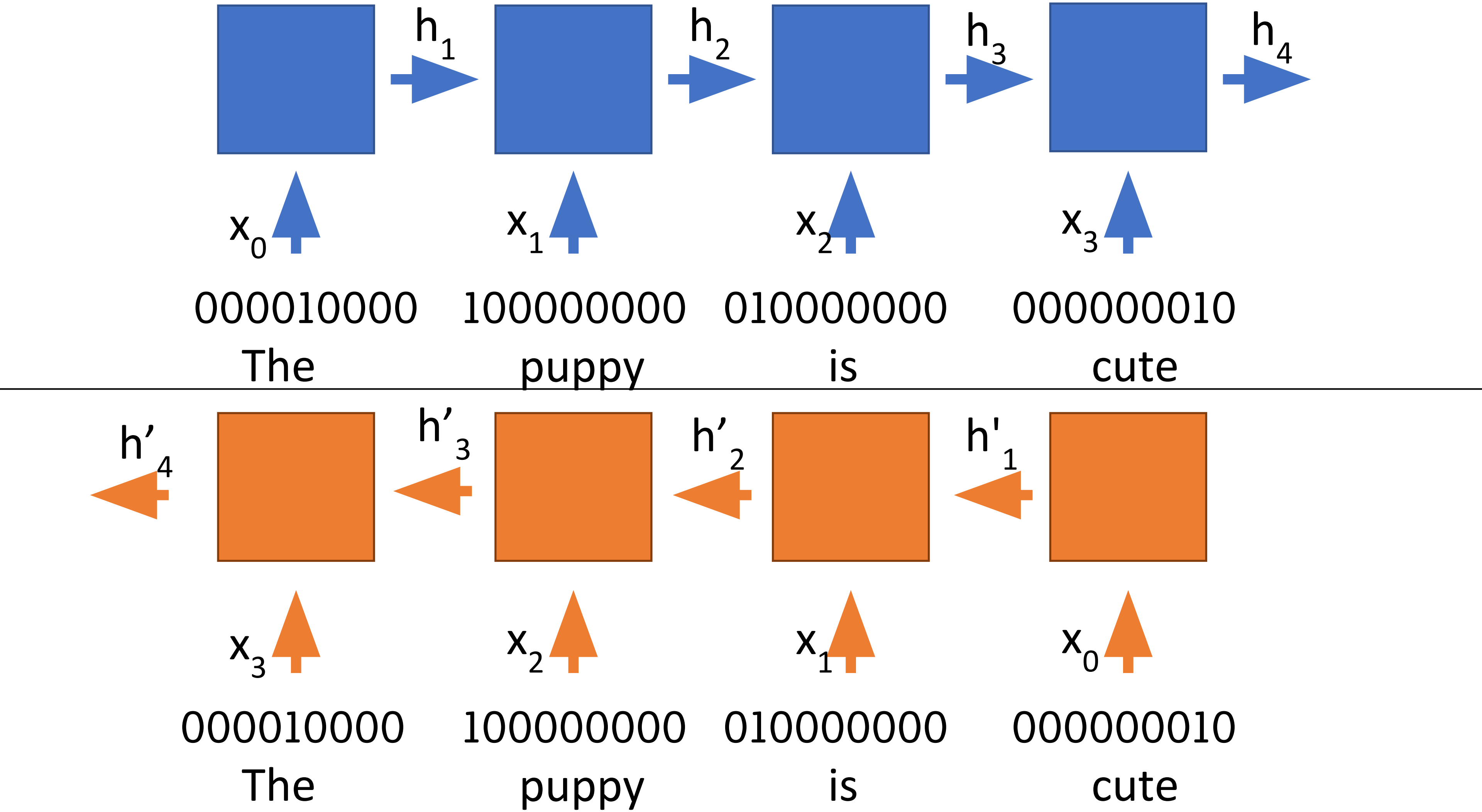
h1
h2
h3
h4
x0
x1
x2
x3
000010000
The
100000000
puppy
010000000
is
000000010
cute



$h_1$
$h_2$
$h_3$
$h_4$
$f(h_4)$ = 'en'
$x_0$
$x_1$
$x_2$
$x_3$
000010000
The
100000000
puppy
010000000
is
000000010
cute


f(h1) -> def. art.
f(h2) -> noun
f(h3) -> verb
f(h4) -> adjective
h1
h2
h3
h4
h1
h2
h3
h4
x0
x1
x2
x3
000010000
The
100000000
puppy
010000000
is
000000010
cute

BIDIRECTIONAL


$h_1$
$h_2$
$h_3$
$h_4$
$x_0$
$x_1$
$x_2$
$x_3$
000010000
100000000
010000000
000000010
The
puppy
is
cute
$h'_4$
$h'_3$
$h'_2$
$h'_1$
$x_3$
$x_2$
$x_1$
$x_0$
000010000
100000000
010000000
000000010
The
puppy
is
cute

# Bidirectional RNN

Concatenate the two hidden representations to produce the bidirectional representation

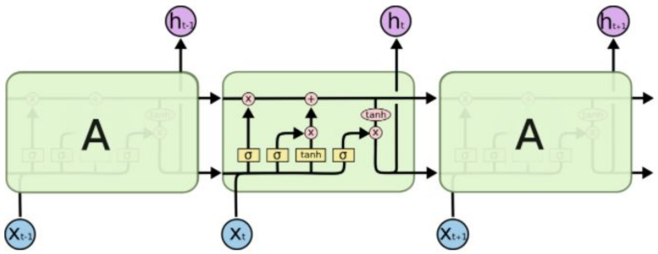
Full sentence: $f([h_4, h'_4])$

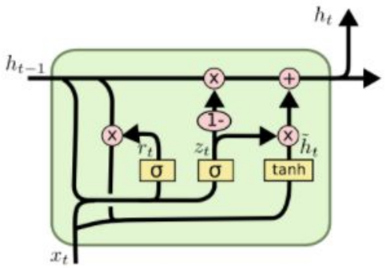
Individual word: $f([h_i, h'_{n-i}])$

# Okay, so RNNs are great!

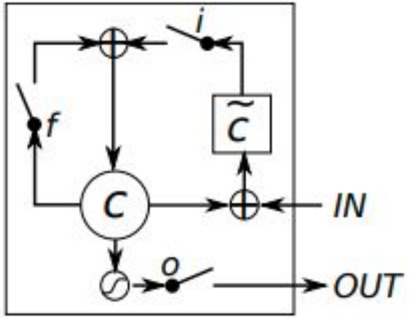
- Except they don’t work
  - (at least for long-term dependencies)
- Vanishing / exploding gradient

LSTM (Long Short Term Memory)

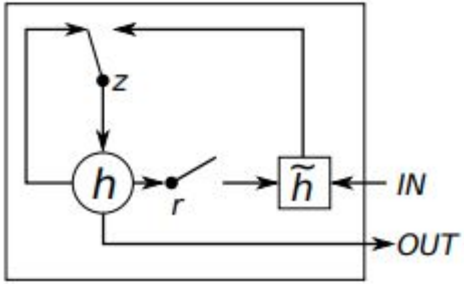


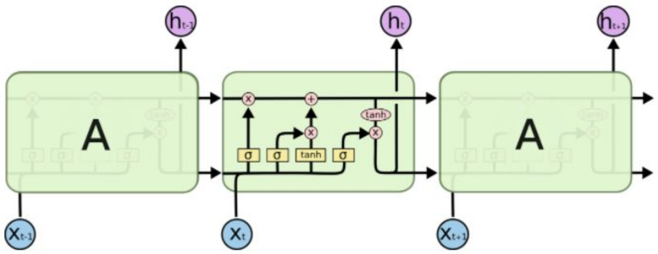
GRU (Gated Recurrent Unit)

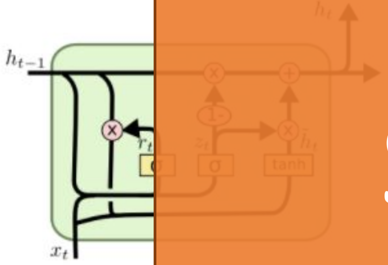



75 other variations



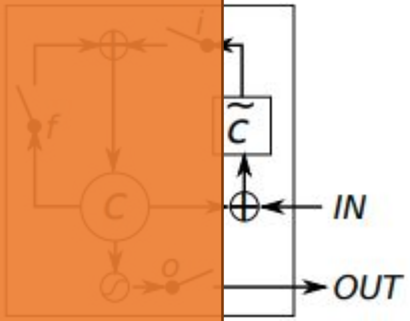
LSTM (Long Short Term Memory)



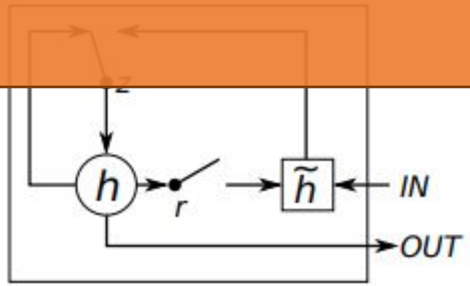




GRU (Gated Recurrent Unit)

# Same basic idea




75 other variations



# Add more neural networks!

- Add “gates” that decide how to balance impact of new input vs hidden state
  - “Remember” gates
  - “Forget” gates
  - “Reset” gates
- Take input and previous state
- Hit ‘em with some weights
- Run it through a sigmoid
- Multiply against $h_i$ or $x_i$
  - Sigmoid values from 0 – 1 to signify how much to keep/forget

# Key Lessons for ML [Domingos, 2012]

- Learning = Representation + Evaluation + Optimization
- **It's generalization that counts: generalize beyond training examples**
- Data alone is not enough: "no free lunch" theorem--No learner can beat random guessing over all possible functions to be learned
- Intuition fails in high dimensions: "curse of dimensionality"
- **More data beats a cleverer algorithm**: Google showed that after providing 300M images for DL image recognition, no flattening of the learning curve was observed.

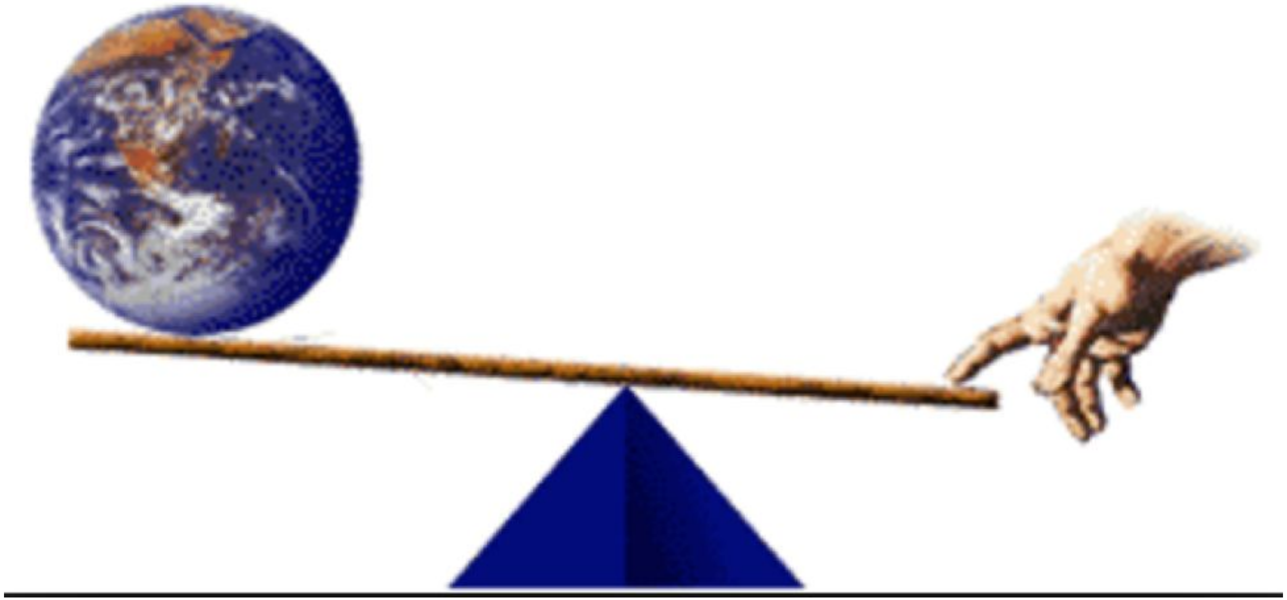
# DI & ML as Synergy

- **ML for effective DI: AUTOMATION, AUTOMATION, AUTOMATION**
  - Automating DI tasks with training data
  - Better understanding of semantics by neural network

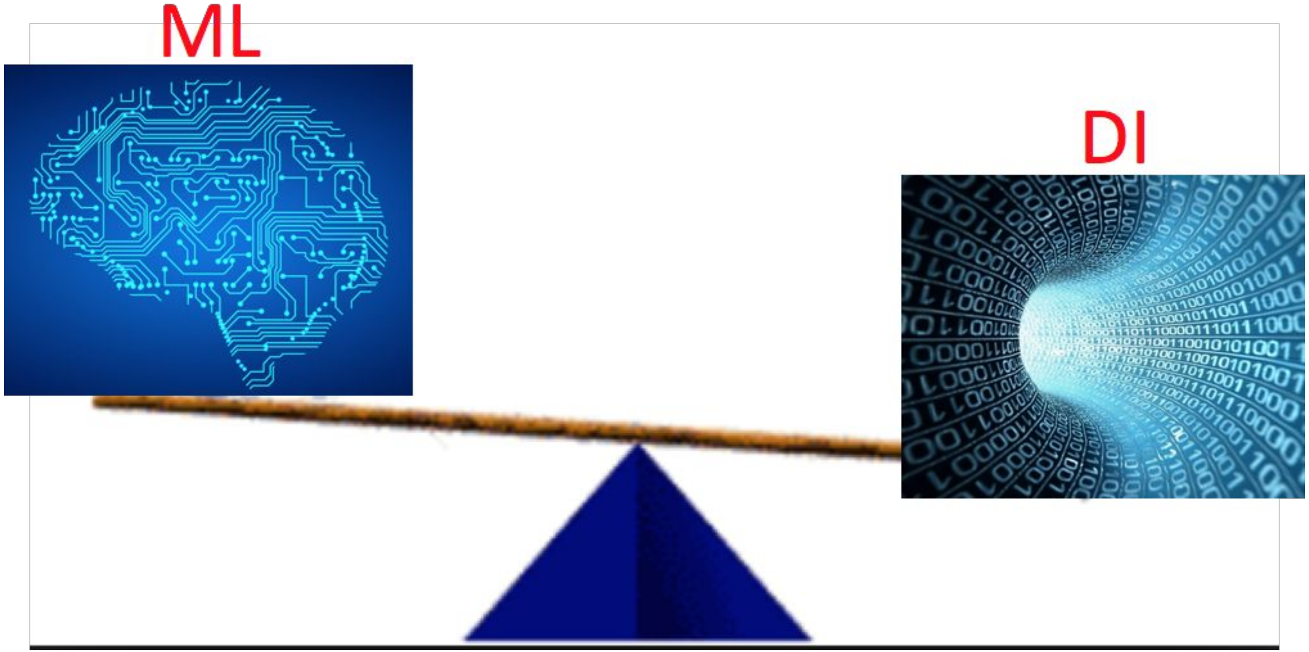
- **DI for effective ML: DATA, DATA, DATA**
  - Create large-scale training datasets from different sources
  - Cleaning of data used for training

# Give me a Fulscrum, I will Move the Earth

-- Archimedes



# Give me a DI funnel, I will Move ML



# Many Systems Where DI & ML Leverage Each Other

NELL

MacroBase

QCRI
معهد قطر لبحوث الحوسبة
Qatar Computing Research Institute
جامعة حمد بن خليفة
HAMAD BIN KHALIFA UNIVERSITY

Magellan

HoloClean

snorkel

Dedupe.io

KNOWLEDGE VAULT

BigGorilla

tamr

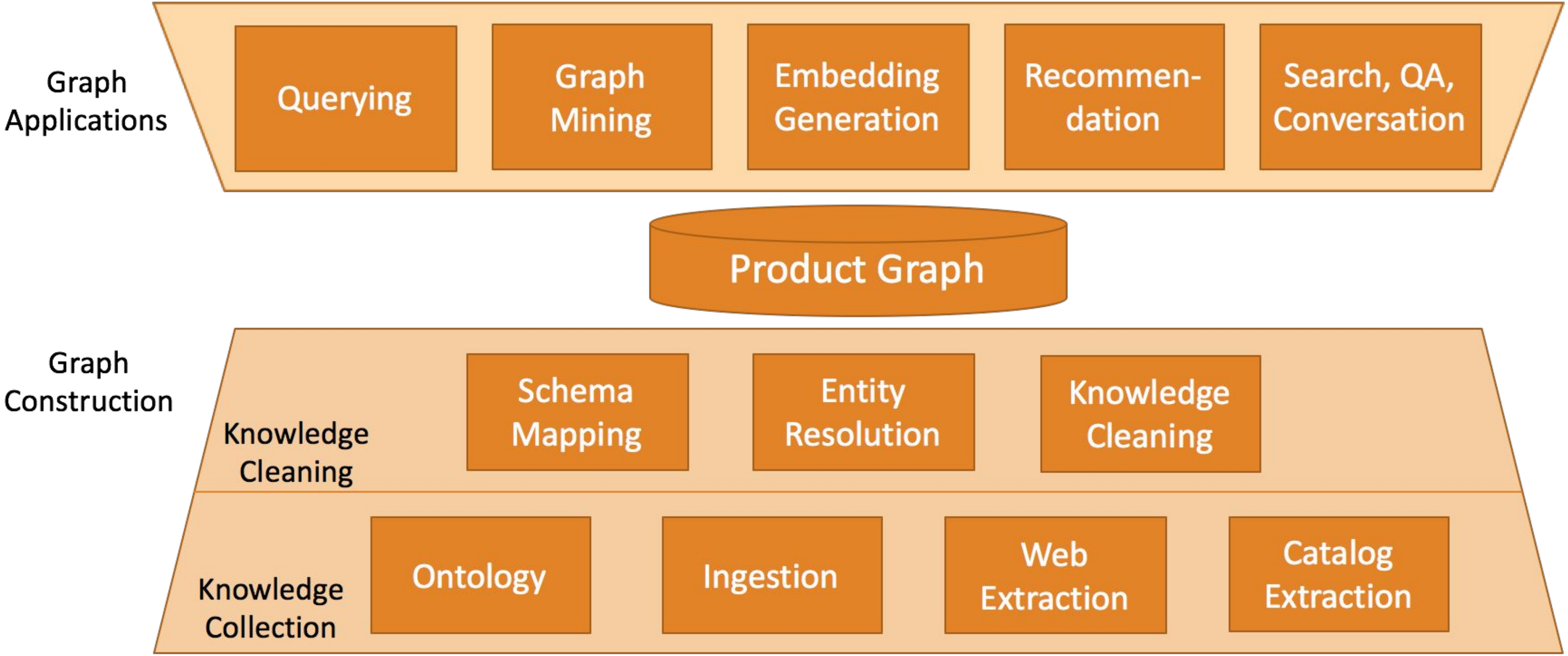
amperity

product graph

TRIFACTA

Increasing number of systems both in industry and academia.

# Example System: Product Graph [Dong, KDD'18]



# Goal of This Tutorial

- **NO-GOALS**
  - Present a comprehensive literature review for all topics we are covering

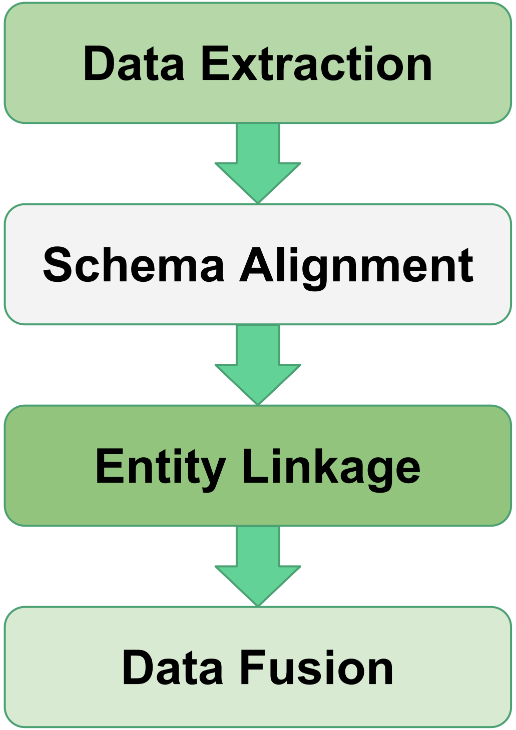
- **GOALS**
  - Present state-of-the-art for DI & ML synergy
  - Show how ML has been transforming DI and vice versa
  - Give some taste on which tool is working best for which tasks
  - Discuss what remains challenging

# Outline

- Part I. Introduction
- Part II. ML for DI
- Part III. DI for ML
- Part IV. Conclusions and research directions

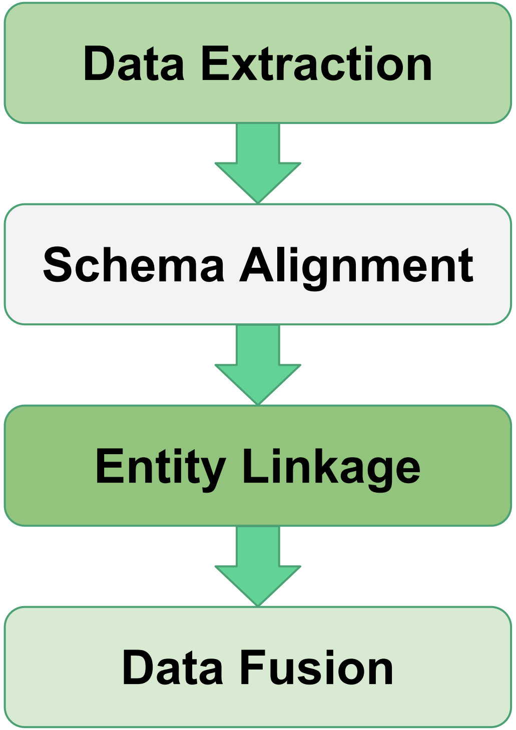
# Data Integration Overview

- Entity linkage: linking records to entities; indispensable when different sources exist
- Data extraction: extracting structured data; important when non-relational data exist
- Data fusion: resolving conflicts; necessary in presence of erroneous data
- Schema alignment: aligning types and attributes; helpful when different relational schemas exist



# Recipe

- Problem definition
- Brief history
- State-of-the-art ML solutions
- Summary w. a short answer

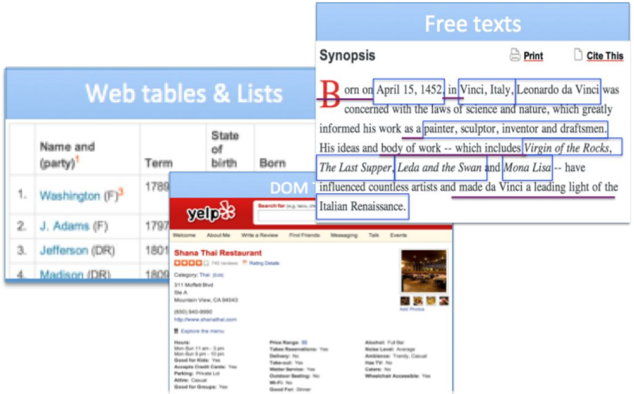


# Theme I. Which ML Model Works Best?

# Which ML Model Works Best?

| ID | NAME | CLASS | MARK | SEX |
|---|---|---|---|---|
| 1 | John Deo | Four | 75 | female |
| 2 | Max Ruin | Three | 85 | male |
| 3 | Arnold | Three | 55 | male |
| 4 | Krish Star | Four | 60 | female |
| 5 | John Mike | Four | 60 | female |
| 6 | Alex John | Four | 55 | male |
| 7 | My John Rob | Fifth | 78 | male |
| 8 | Asruid | Five | 85 | male |
| 9 | Tes Qry | Six | 78 | male |
| 10 | Big John | Four | 55 | female |

Tree-based models

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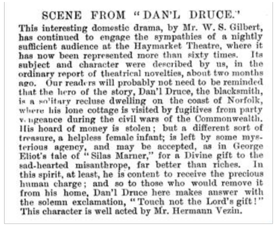


SCENE FROM "DAN'L DRUCE."

This interesting domestic drama, by Mr. W. S. Gilbert, has continued to engage the sympathies of a nightly sufficient audience at the Haymarket Theatre, where it has now been represented more than sixty times. Its subject and character were described by us, in the ordinary report of theatrical novelties, about two months ago. Our readers will probably not need to be reminded that the hero of the story, Dan'l Druce, the blacksmith, is a solitary recluse dwelling on the coast of Norfolk, where his lone cottage is visited by fugitives from party vengeance during the civil wars of the Commonwealth. His hoard of money is stolen; but a different sort of treasure, a helpless female infant; is left by some mysterious agency, and may be accepted, as in George Eliot's tale of "Silas Marner," for a Divine gift to the sad-hearted misanthrope, far better than riches. In this spirit, at least, he is content to receive the precious human charge; and so to those who would remove it from his home, Dan'l Druce here makes answer with the solemn exclamation, "Touch not the Lord's gift!" This character is well acted by Mr. Hermann Vezin.

Neural network

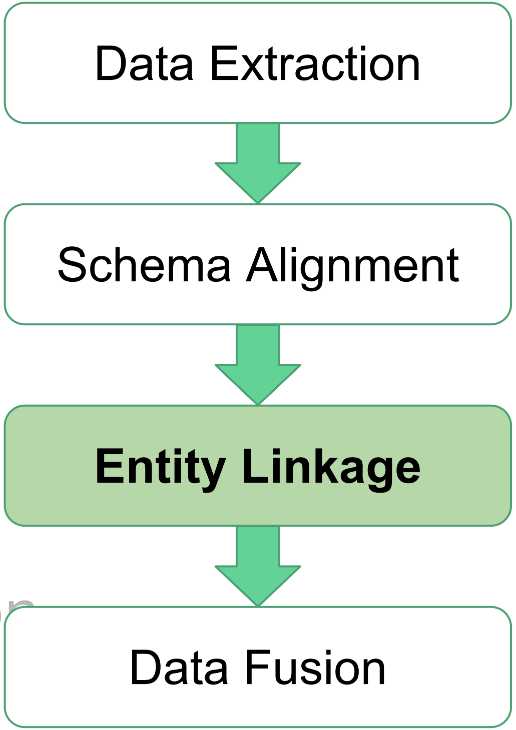
# Theme II. Does Supervised Learning Apply to DI?

- **Supervised learning has made a big splash recently in many fields**

- **However, it is hard to bluntly apply supervised learning to DI tasks**
  - Our goal is to integrate data from many different data sources in different domains
  - The different sources present different data features and distributions
  - Collecting training labels for each source is a huge cost

# Outline

- Part I. Introduction
- Part II. ML for DI
  - ML for entity linkage
  - ML for data extraction
  - ML for data fusion
  - ML for schema alignment
- Part III. DI for ML
- Part IV. Conclusions and research direction



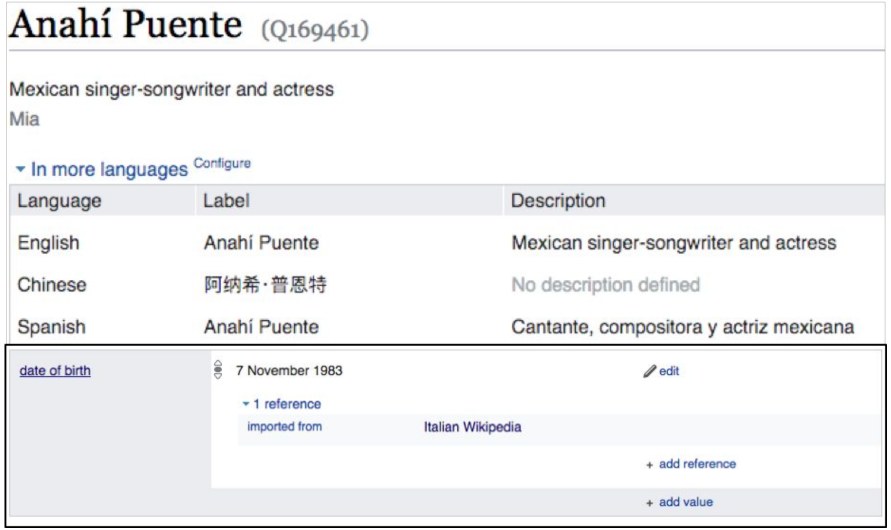
# What is Entity Linkage?

- Definition: Partition a given set $\mathcal{R}$ of records, such that each partition corresponds to a distinct real-world entity.

## Are they the same entity?

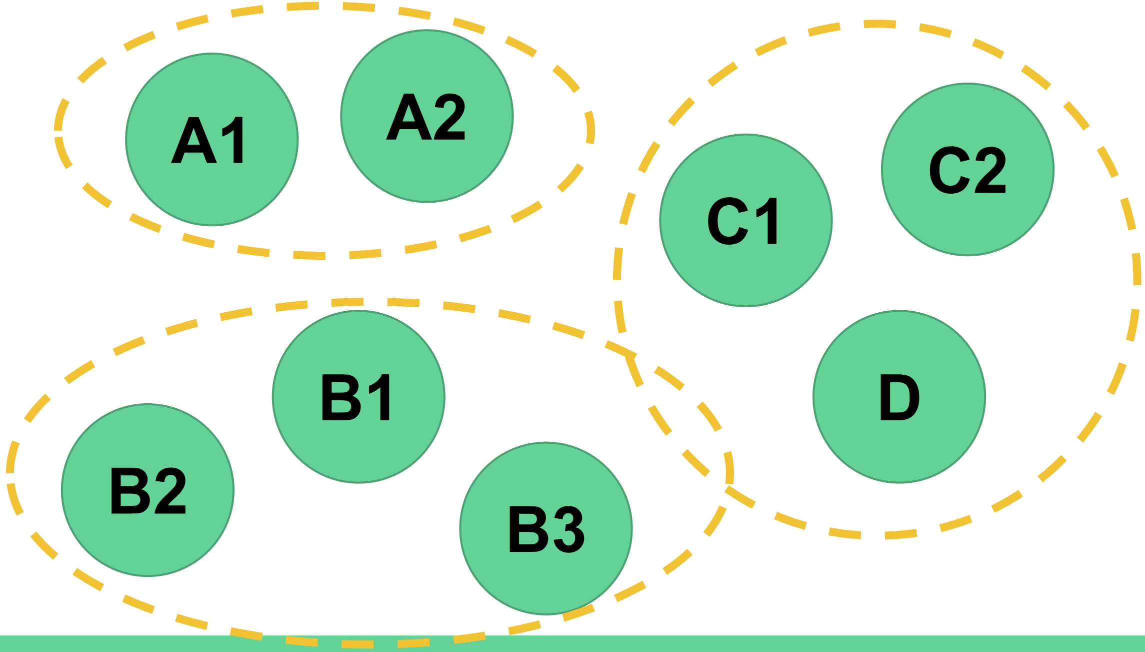
IMDB

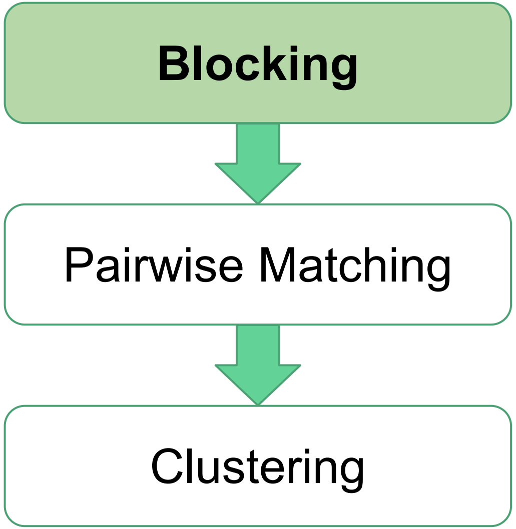

WikiData



# Quick Tour for Entity Linkage

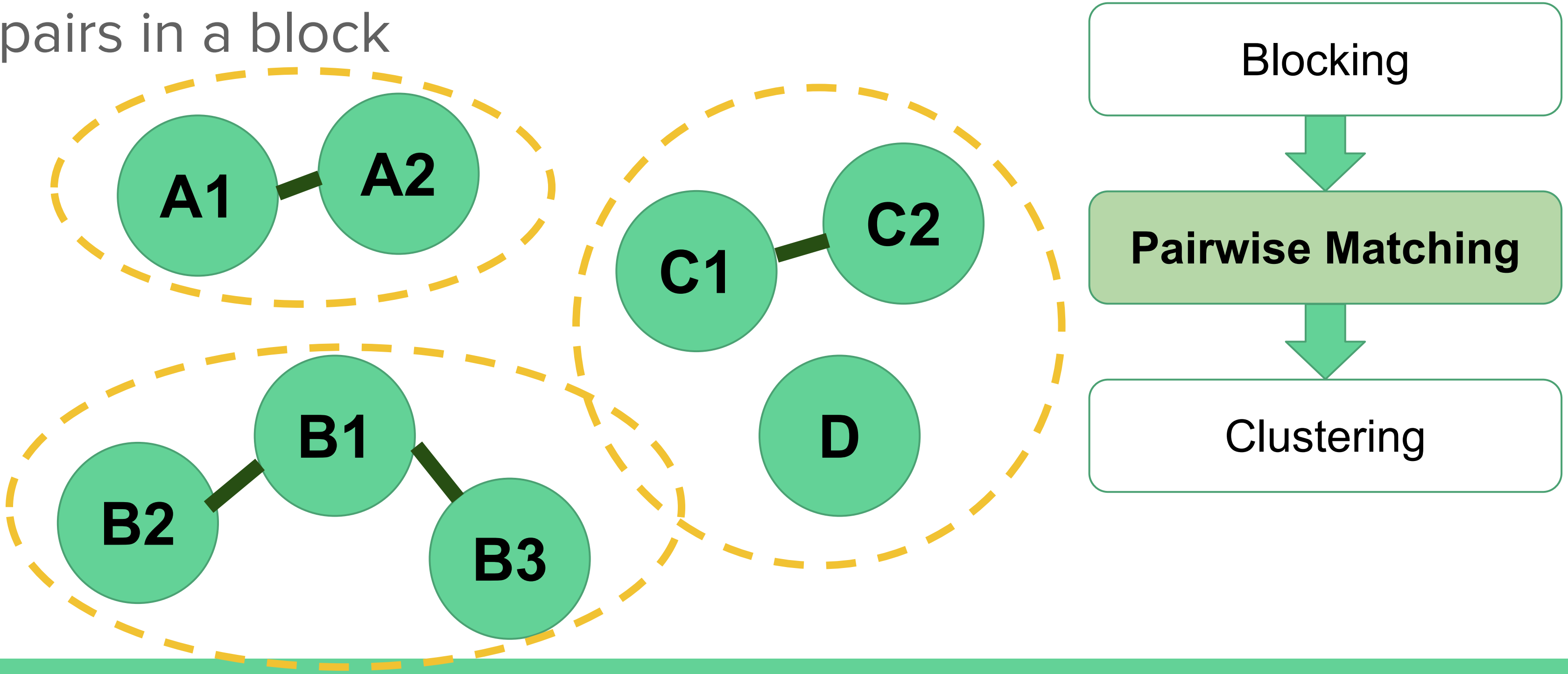
- **Blocking**: efficiently create small blocks of similar records



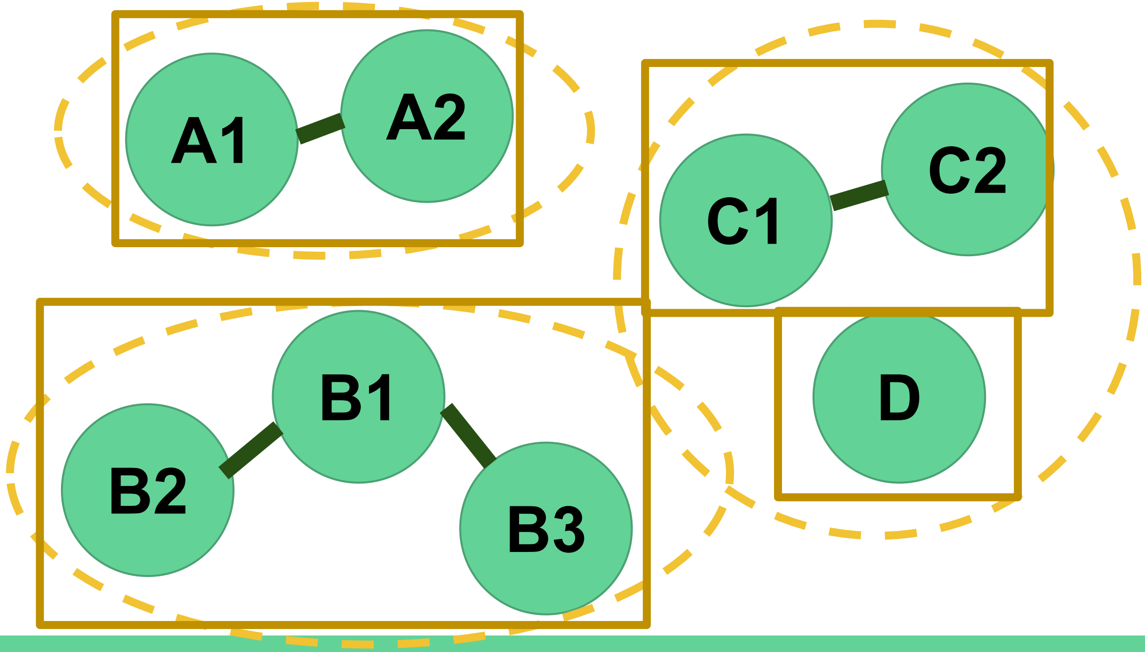
# Quick Tour for Entity Linkage

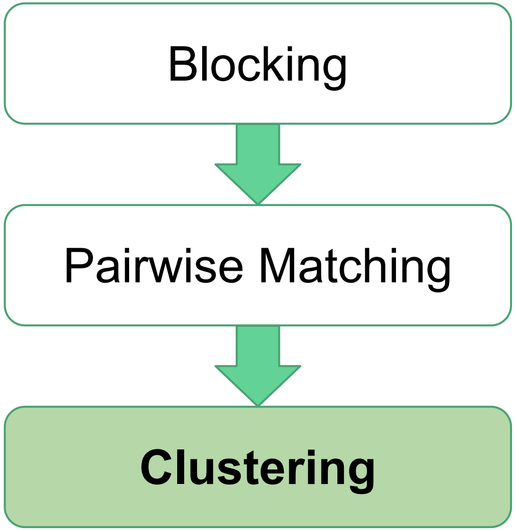
- **Pairwise matching**: compare all record pairs in a block



# Quick Tour for Entity Linkage

- **Clustering**: group records into entities



# 50 Years of Entity Linkage

1969 (Pre-ML)

**Rule-based and stats-based**

- Blocking: e.g., same name
- Matching: e.g., avg similarity of attribute values
- Clustering: e.g., transitive closure, etc.

~2000 (Early ML)

**Sup / Unsup learning**

- Matching: Decision tree, SVM
  **F-msr: 70%-90% w. 500 labels**
- Clustering: Correlation clustering, Markov clustering

~2015 (ML)

**Supervised learning**

- Random forest for matching
  **F-msr: >95% w. ~1M labels**
- Active learning for blocking & matching
  **F-msr: 80%-98% w. ~1000 labels**

2018 (Deep ML)

**Deep learning**

- Deep learning
- Entity embedding

# Rule-Based Solution

**Rule-based and stats-based**

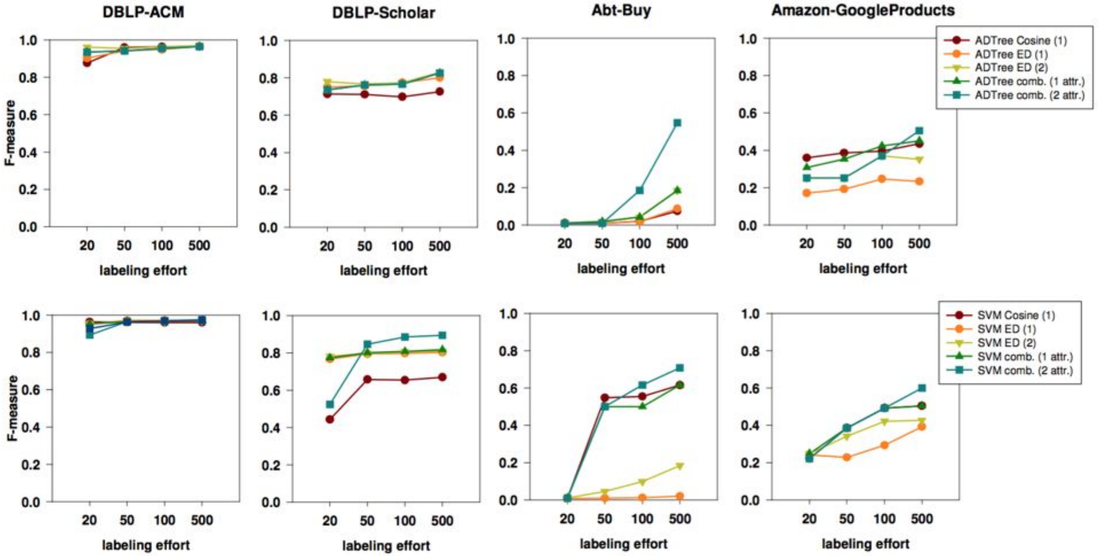
- Blocking: e.g., same name
- Matching: e.g., avg similarity of attribute values
- Clustering: e.g., transitive closure, etc.

**1969 (Pre-ML)**

- [Fellegi and Sunter, 1969]
  - Match: sim(r, r') > $\theta_h$
  - Unmatch: sim(r, r') < $\theta_l$
  - Possible match: $\theta_l$ < sim(r, r') < $\theta_h$

# Early ML Models

- [Köpcke et al, VLDB'10]




**~2000 (Early ML)**

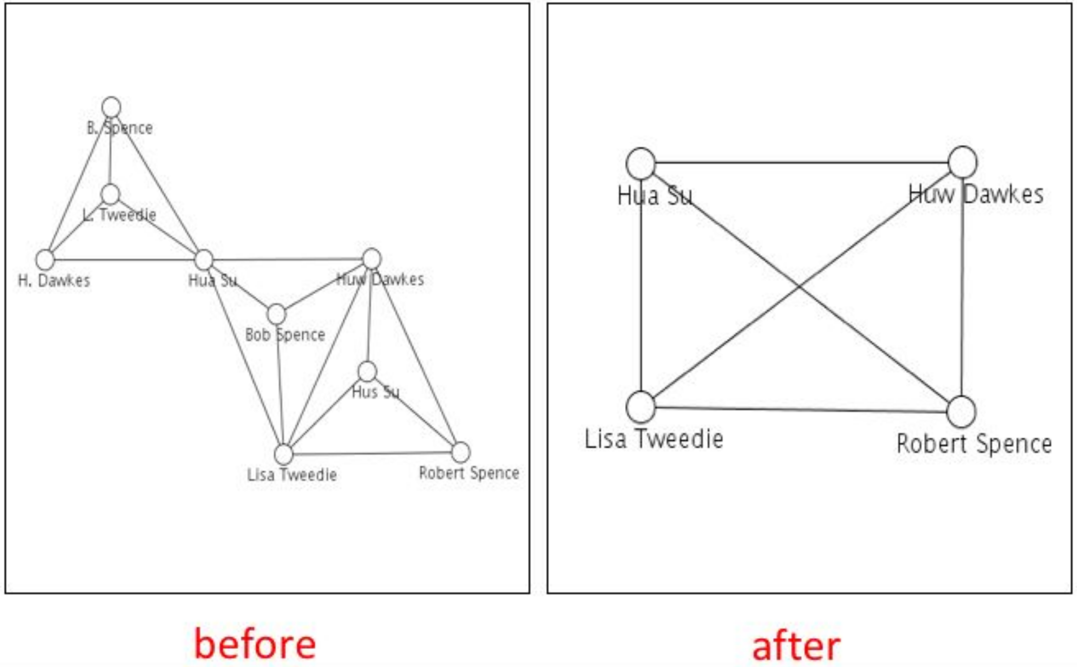
**Sup / Unsup learning**

- Matching: Decision tree, SVM
  **F-msr: 70%-90% w. 500 labels**
- Clustering: Correlation clustering, Markov clustering

# Collective Entity Resolution: Beyond Pairs

- Collective reasoning across entities.
- Constraints across entities:
  - Aggregate constraints
  - Transitivity, Exclusivity
  - Functional dependencies
- Use of probabilistic graphical models, PSL, MLN, to capture such domain knowledge

Out of the scope of this tutorial. For details: See tutorial by Getoor and Machanavajjhala, KDD, 2013.




[Example by Getoor and Machanavajjhala]

# State-of-the-Art ML Models [Dong, KDD'18]

**Supervised learning**

- Random forest for matching
  **F-msr: >95% w. ~1M labels**
- AL for blocking & matching
  **F-msr: 80%-98% w. ~1000 labels**

**~2015 (ML)**

- Features: attribute similarity measured in various ways. E.g.,
  - string sim: Jaccard, Levenshtein
  - number sim: absolute diff, relative diff
- ML models on Freebase vs. IMDb
  - Logistic regression: Prec=0.99, Rec=0.6
  - Random forest: Prec=0.99, Rec=0.99

# State-of-the-Art ML Models [Dong, KDD'18]

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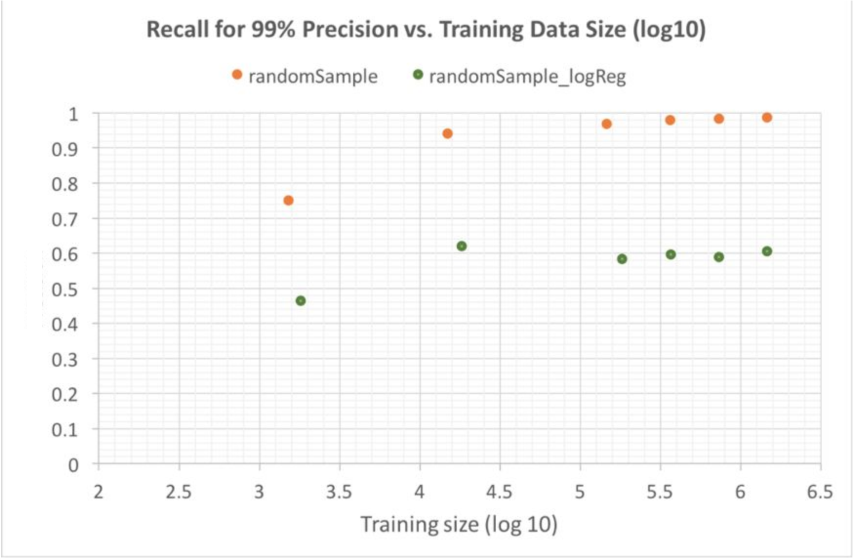
- Expt 1. IMDb vs. Freebase
  - Logistic regression: Prec=0.99, Rec=0.6
  - Random forest: Prec=0.99, Rec=0.99



# State-of-the-Art ML Models [Dong, KDD'18]

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**~2015 (ML)**

- Features: attribute similarity measured in various ways. E.g.,
  - name sim: Jaccard, Levenshtein
  - age sim: absolute diff, relative diff
- ML models on Freebase vs. IMDb
  - Logistic regression: Prec=0.99, Rec=0.6
  - Random forest: Prec=0.99, Rec=0.99
  - XGBoost: marginally better, but sensitive to hyper-parameters

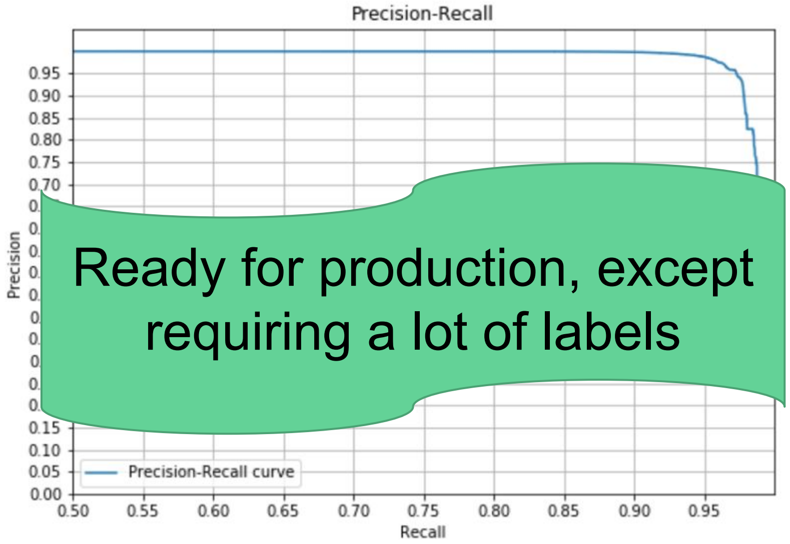
# State-of-the-Art ML Models [Dong, KDD'18]

**Supervised learning**

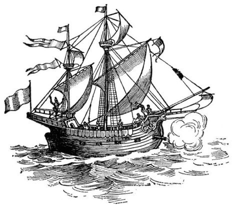
- Random forest for matching
  **F-msr: >95% w. ~1M labels**
- AL for blocking & matching
  **F-msr: 80%-98% w. ~1000 labels**

**~2015 (ML)**

- Expt 2. IMDb vs. Amazon movies
  - 200K labels, ~150 features
  - Random forest: Prec=0.98, Rec=0.95



# State-of-the-Art ML Models [Das et al., SIGMOD'17]



**Magellan**

**Supervised learning**

- Random forest for matching
  **F-msr: >95% w. ~1M labels**
- AL for blocking & matching
  **F-msr: 80%-98% w. ~1000 labels**

**~2015 (ML)**

- Falcon: apply active learning both for blocking and for matching; ~1000 labels

| Dataset | Accuracy (%) | | | Cost (# Questions) |
|---|---|---|---|---|
| | $P$ | $R$ | $F_1$ | |
| Products | 90.9 | 74.5 | 81.9 | \$57.6 (960) |
| Songs | 96.0 | 99.3 | 97.6 | \$54.0 (900) |
| Citations | 92.0 | 98.5 | 95.2 | \$65.5 (1087) |

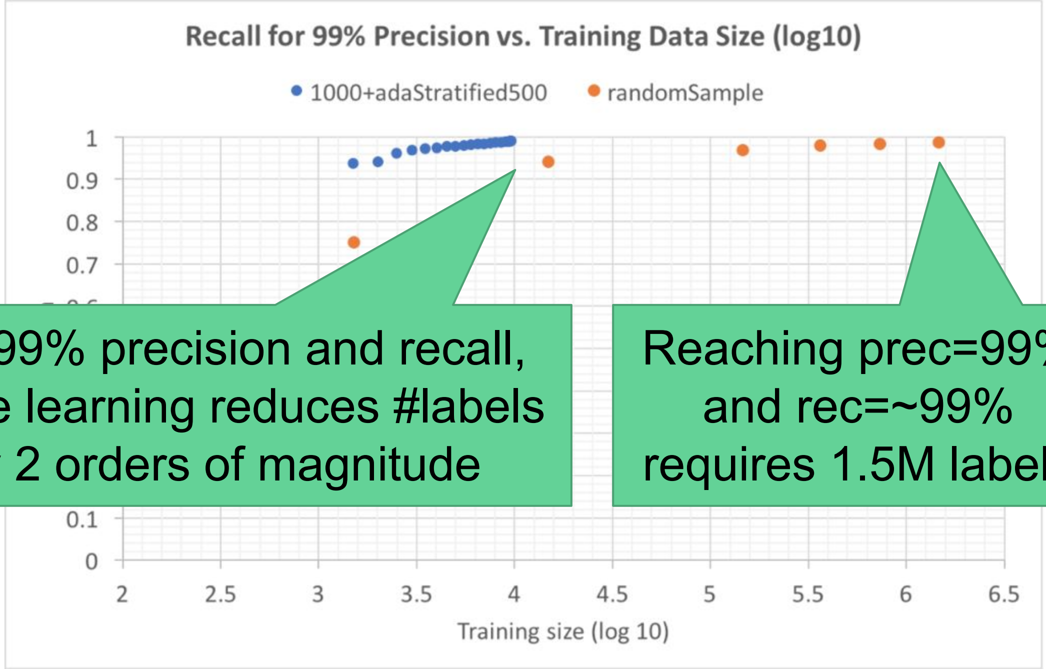
# State-of-the-Art ML Models [Dong, KDD'18]

**Supervised learning**

- Random forest for matching
  **F-msr: >95% w. ~1M labels**
- AL for blocking & matching
  **F-msr: 80%-98% w. ~1000 labels**

**~2015 (ML)**

- Apply active learning to minimize #labels




For 99% precision and recall, active learning reduces #labels by 2 orders of magnitude

Reaching prec=99% and rec=~99% requires 1.5M labels

# Deep Learning Models [Mudgal et al., SIGMOD'18]

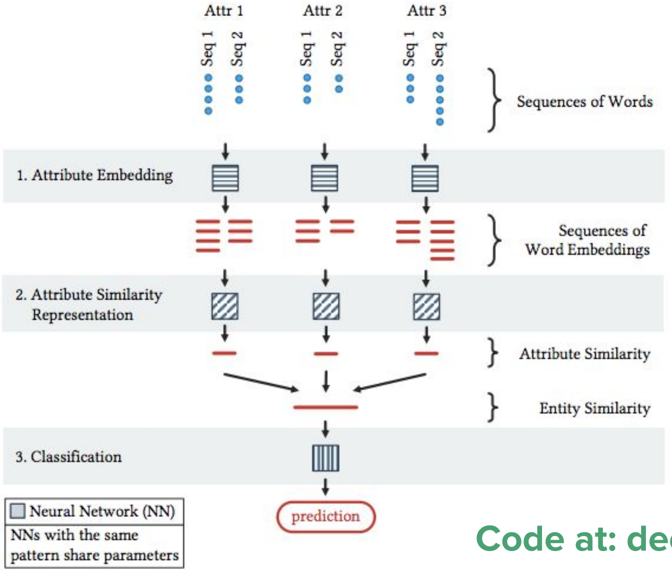
Magellan

- Embedding on similarities
- Similar performance for structured data; Significant improvement on texts and dirty data

## 2018 (Deep ML)

**Deep learning**

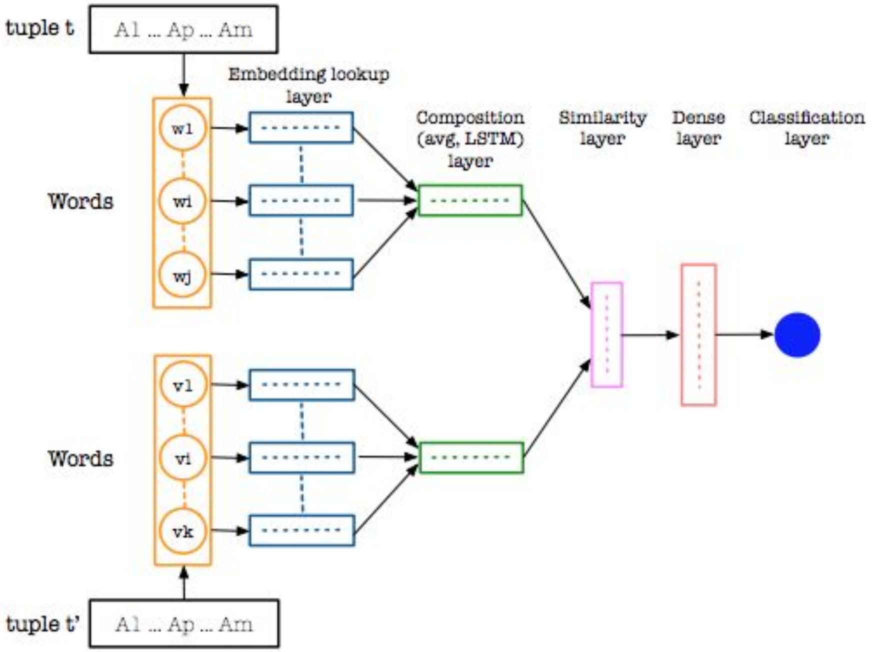
- Deep learning
- Entity embedding




Code at: deepmatcher.ml

# Deep Learning Models [Ebraheem et al., VLDB'18]

- Embedding on entities
- Outperforming existing solution



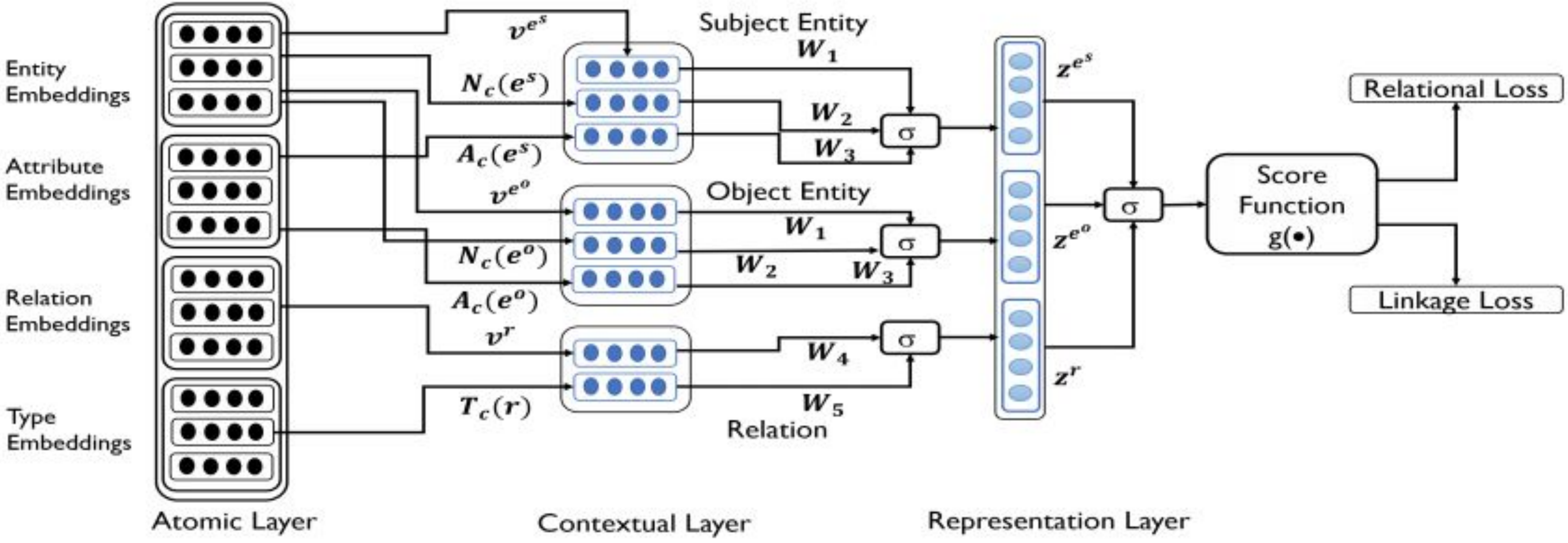

## 2018 (Deep ML)

**Deep learning**

- Deep learning
- Entity embedding

# Deep Learning Models [Trivedi et al., ACL'18]

- LinkNBed: Embeddings for entities as in knowledge embedding



# Deep Learning Models [Trivedi et al., ACL'18]

2018 (Deep ML)

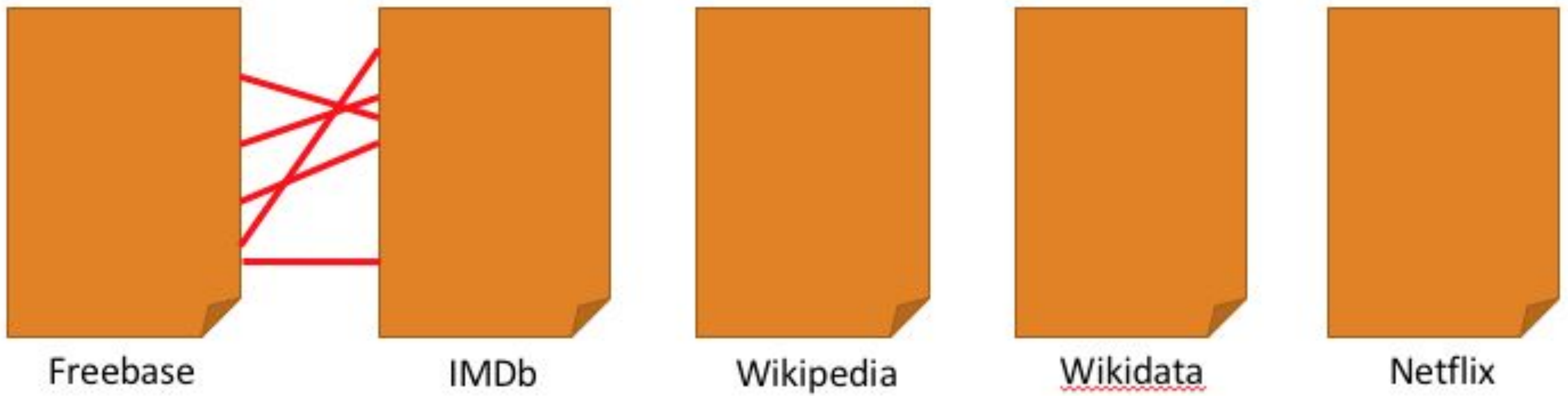
**Deep learning**

- Deep learning
- Entity embedding

- LinkNBed: Embeddings for entities as in knowledge embedding
- Performance better than previous knowledge embedding methods, but not comparable to random forest
- Enable linking different types of entities

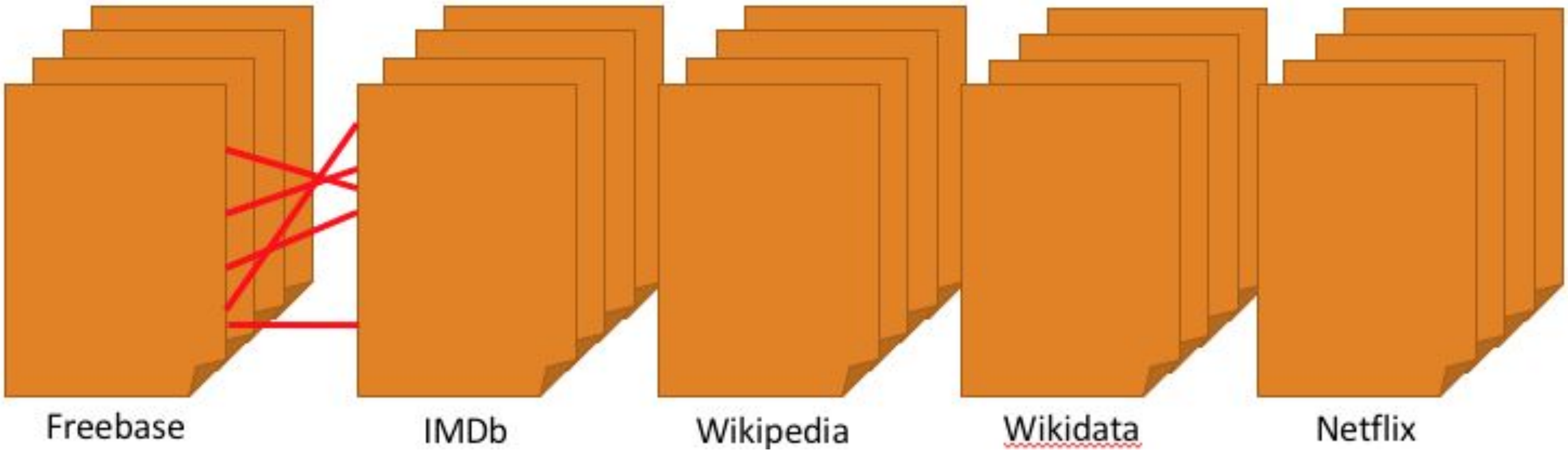
# Challenges in Applying ML on EL

- **How can we obtain abundant training data for many types, many sources, and dynamically evolving data??**
- From two sources to multiple sources



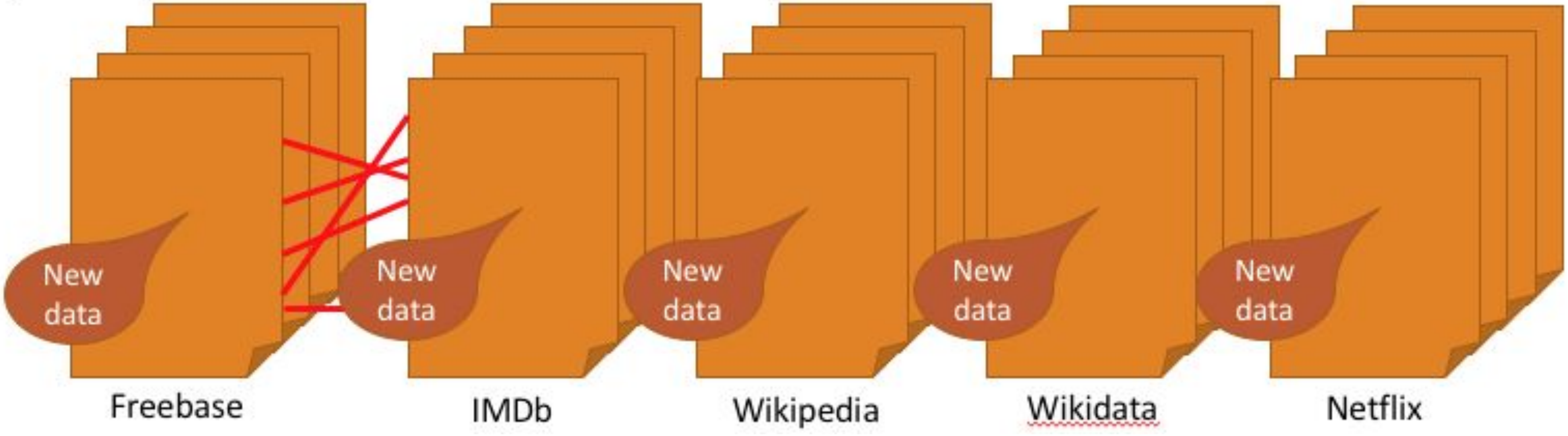
# Challenges in Applying ML on EL

- **How can we obtain abundant training data for many types, many sources, and dynamically evolving data??**
- From one entity type to multiple types



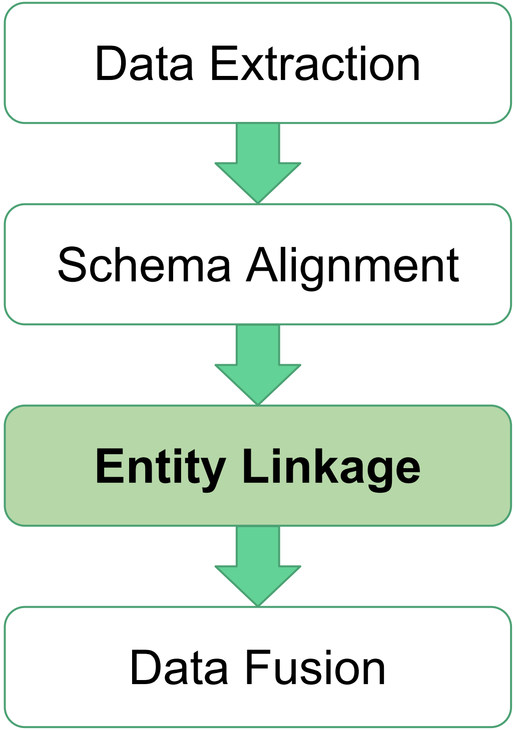
# Challenges in Applying ML on EL

- **How can we obtain abundant training data for many types, many sources, and dynamically evolving data??**
- From static data to dynamic data



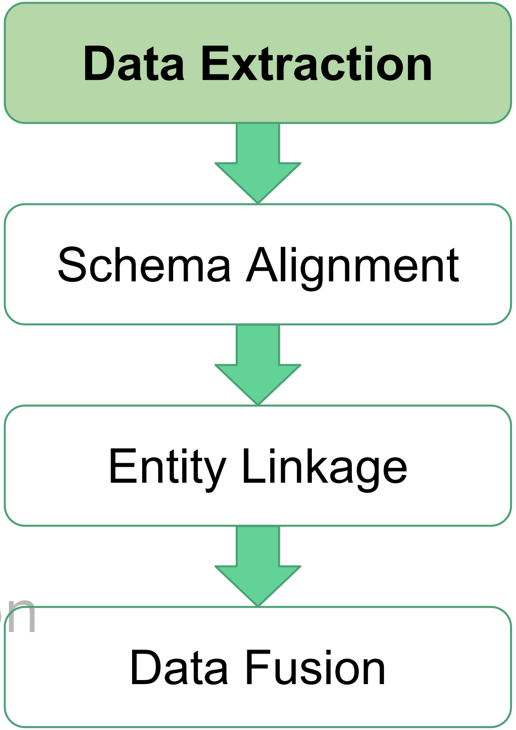
# Recipe for Entity Linkage

- Problem definition: **Link references to the same entity**
- Short answers
  - **RF w. attribute-similarity features**
  - **DL to handle texts and noises**
  - **End-to-end solution is future work**

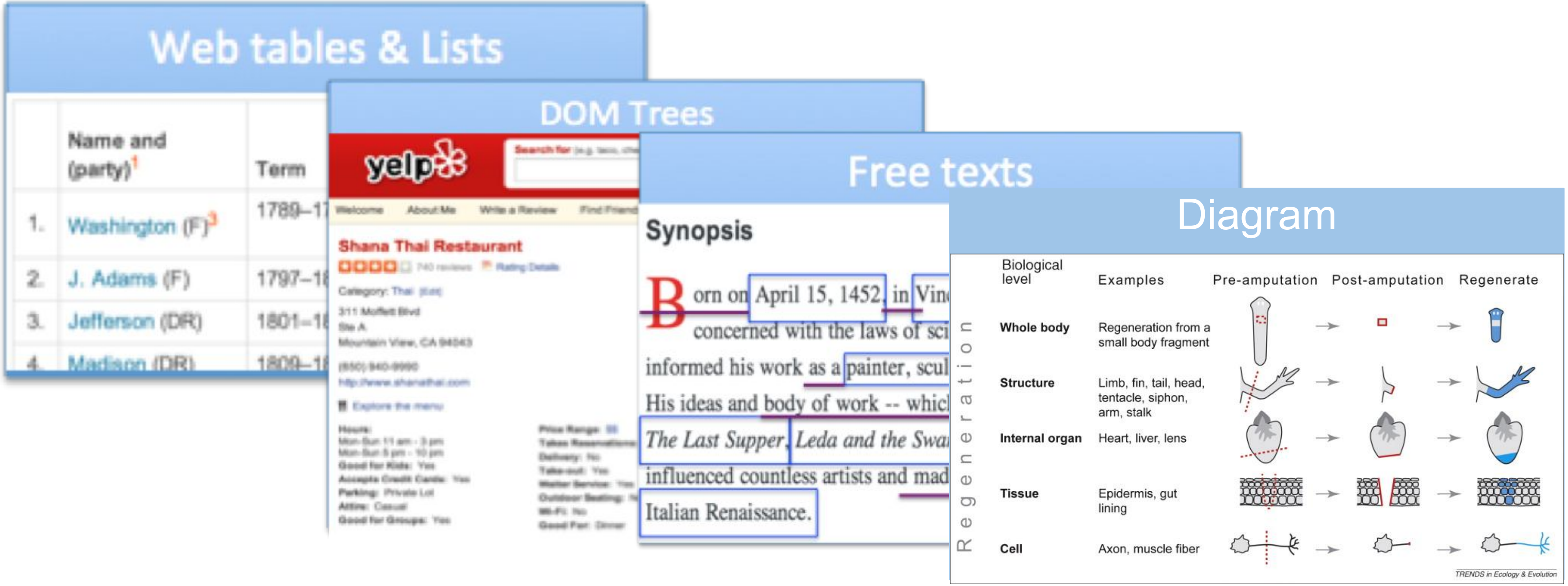
# Outline

- Part I. Introduction
- Part II. ML for DI
  - ML for entity linkage
  - ML for data extraction
  - ML for data fusion
  - ML for schema alignment
- Part III. DI for ML
- Part IV. Conclusions and research direction



# What is Data Extraction?

- Definition: Extract structured information, e.g., (entity, attribute, value) triples, from semi-structured data or unstructured data.



# Three Types of Data Extraction

- **Closed-world extraction**: align to existing entities and attributes; e.g., (ID_Obama, place_of_birth, ID_USA)

- **ClosedIE**: align to existing attributes, but extract new entities; e.g., (“Xin Luna Dong”, place_of_birth, “China”)

- **OpenIE**: not limited by existing entities or attributes; e.g., (“Xin Luna Dong”, “was born in”, “China”), (“Luna”, “is originally from”, “China”)

# 35 Years of Data Extraction

**Early Extraction**

- Rule-based: Hearst pattern, IBM System T
- Tasks: IS-A, events

**1992 (Rule-based)**

**~2005 (Rel. Ex.)**

**Relation extraction from texts**

- NER→EL→RE
  - Feature based: LR, SVM
  - Kernel based: SVM
- Distant supervision
- OpenIE

**Extraction from semi-structured data**

- WebTables: search, extraction
- DOM tree: wrapper induction

**2008 (Semi-stru)**

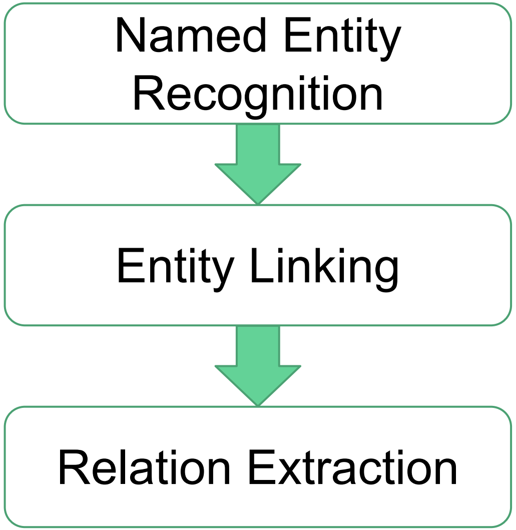
**2013 (Deep ML)**

**Deep learning**

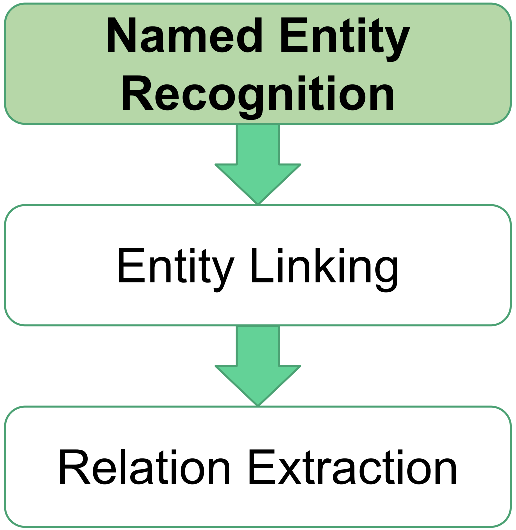
- Use RNN, CNN, attention for RE
- Data programming / Heterogeneous learning
- Revisit DOM extraction

# Extraction from Texts: Quick Tour

Bill Gates founded Microsoft in 1975.



# Extraction from Texts: Quick Tour

# Extraction from Texts: Quick Tour

Bill Gates founded Microsoft in 1975.

Named Entity Recognition

**Entity Linking**

Relation Extraction

Entity **linkage**: linking two structured records

Entity **linking**: linking a phrase in texts to an entity in a reference list (e.g., knowledge graph)

# Extraction from Texts: Quick Tour

Bill Gates founded Microsoft in 1975.

isFounder

Microsoft

We focus on Relation Extraction in the rest of the tutorial.

Named Entity Recognition

Entity Linking

**Relation Extraction**

# Extraction from Texts: Feature Based [Zhou et al., ACL'05]

**~2005 (Rel. Ex.)**

**Relation extraction from texts**

- NER→EL→RE
  - Feature based: LR, SVM
  - Kernel based: SVM
- Distant supervision
- OpenIE

- **Models**
  - Logistic regression
  - SVM (Support Vector Machine)
- **Features**
  - Lexical: entity, part-of-speech, neighbor
  - Syntactic: **chunking**, parse tree
  - Semantic: concept hierarchy, entity class
- **Results**
  - Prec=~60%, Rec=~50%

# Extraction from Texts: Feature Based [Zhou et al., ACL'05]

**~2005 (Rel. Ex.)**

**Relation extraction from texts**

- NER→EL→RE
  - Feature based: LR, SVM
  - Kernel based: SVM
- Distant supervision
- OpenIE

| Features | P | R | F |
|---|---|---|---|
| Words | 69.2 | 23.7 | 35.3 |
| +Entity Type | 67.1 | 32.1 | 43.4 |
| +Mention Level | 67.1 | 33.0 | 44.2 |
| +Overlap | 57.4 | 40.9 | 47.8 |
| +Chunking | 61.5 | 46.5 | 53.0 |
| +Dependency Tree | 62.1 | 47.2 | 53.6 |
| +Parse Tree | 62.3 | 47.6 | 54.0 |
| +Semantic Resources | 63.1 | 49.5 | 55.5 |

Table 2: Contribution of different features over 43 relation subtypes in the test data

Major Lift

# Extraction from Texts: Kernel Based [Mengqiu Wang, IJCNLP'08]

~2005 (Rel. Ex.)

**Relation extraction from texts**

- NER→EL→RE
  - Feature based: LR, SVM
  - Kernel based: SVM
- Distant supervision
- OpenIE

- **Models**
  - SVM (Support Vector Machine)
- **Kernels**
  - Subsequence
  - Dependency tree
  - **Shortest dependency path**
  - Convolution dependency

# Extraction from Texts: Kernel Based [Mengqiu Wang, IJCNLP'08]

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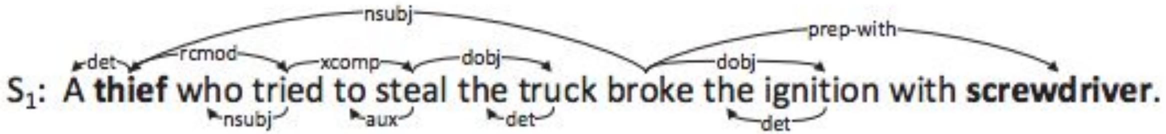
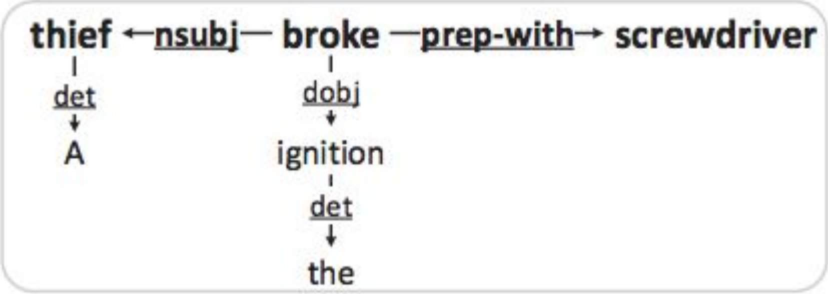



Dependency tree




Shortest dependency path

# Extraction from Texts: Kernel Based [Mengqiu Wang, IJCNLP'08]

**~2005 (Rel. Ex.)**

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- OpenIE

- **Models**
  - SVM (Support Vector Machine)
- **Kernels**
  - Subsequence
  - Dependency tree
  - **Shortest dependency path**
  - Convolution dependency
- **Results**
  - Prec=~70%, Rec=~40%

# Extraction from Texts: Kernel Based [Mengqiu Wang, IJCNLP'08]

**~2005 (Rel. Ex.)**

**Relation extraction from texts**

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  - Feature based: LR, SVM
  - Kernel based: SVM
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| kernel method | 5-fold CV on ACE 2003 Precision | Recall | F1 |
|---|---|---|---|
| subsequence | 0.703 | **0.389** | 0.546 |
| dependency tree | 0.681 | 0.290 | 0.485 |
| shortest path | **0.747** | 0.376 | **0.562** |

Table 1: Results of different kernels on ACE 2003 training set using 5-fold cross-validation.

# Extraction from Texts: Deep Learning

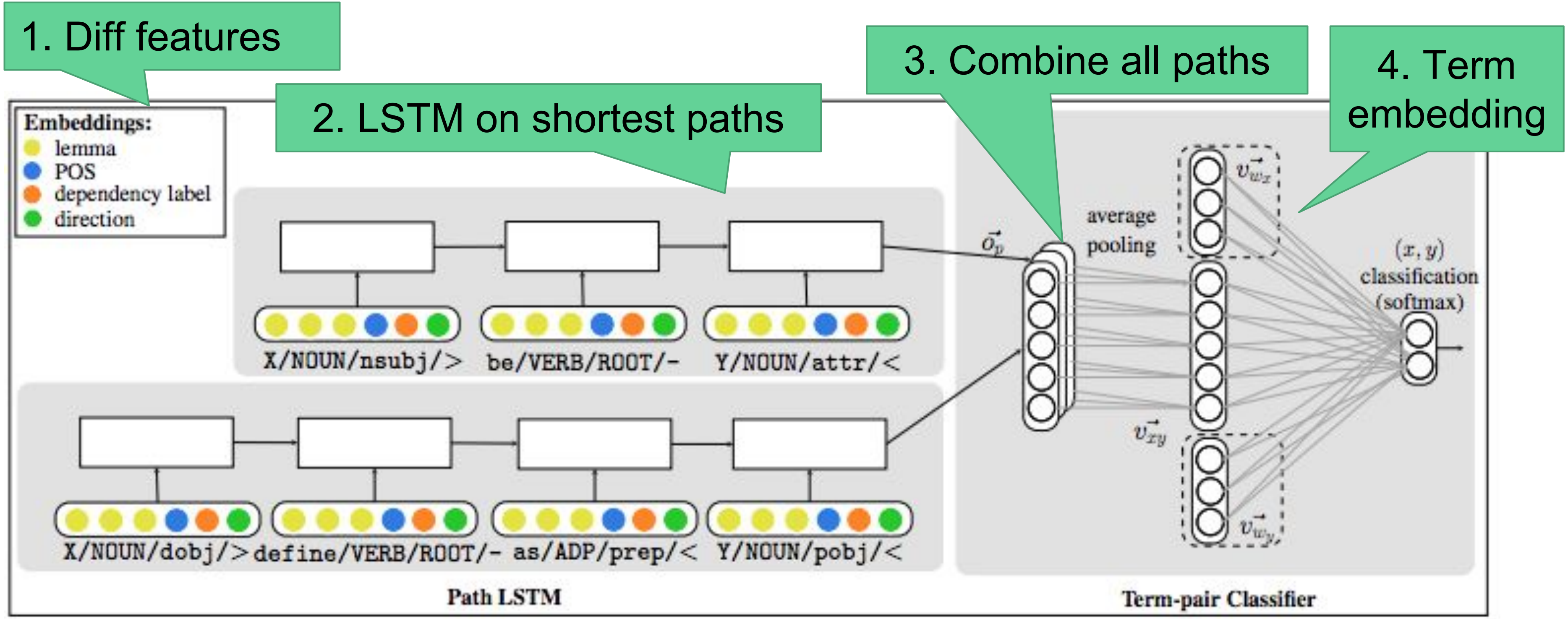
**2013 (Deep ML)**

**Deep learning**

- Use RNN, CNN, attention for RE
- Data programming / Heterogeneous learning
- Revisit DOM extraction

- **Same intuitions, different models**
  - (2012-13) Recursive NN: dependency tree
    [Socher et al., EMNLP'12] [Hashimoto et al., EMNLP'13]
  - (2014-15) CNN: shortest dependency path
    [Zeng et al., COLING'14][Liu et al., ACL'15]
  - (2015+) LSTM: shortest dependency path, lexical/syntactic/semantic features
    [Xu et al., EMNLP'15][Shwartz et al., ACL'16]
    [Nguyen, NAACL'16]

# Example System: HyperNET [Shwartz et al., ACL'16]




**Quality in identifying hypernyms:** Prec = 0.9, Rec = 0.9

# Label Generation for Extraction Training

Where are training labels from?

**~2005 (Rel. Ex.)**

**Relation extraction from texts**

- NER→EL→RE
  - Feature based: LR, SVM
  - Kernel based: SVM
- Distant supervision
- OpenIE

- **Semi-supervised learning**
  - Iterative extraction [Carlson et al., AAAI'10]
    Use new extractions to retrain models
    E.g., NELL

| Iterations | Estimated Precision (%) | # Promotions |
|---|---|---|
| 1–22 | 90 | 88,502 |
| 23–44 | 71 | 77,835 |
| 45–66 | 57 | 76,116 |

# Label Generation for Extraction Training

Where are training labels from?

~2005 (Rel. Ex.)

**Relation extraction from texts**

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  - Feature based: LR, SVM
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- **Semi-supervised learning**
  - Iterative extraction [Carlson et al., AAAI'10]
    Use new extractions to retrain models
    E.g., NELL
- **Weak learning**
  - Distant supervision [Mintz et al., ACL'09]
    Rule-based annotation with seed data
    E.g., DeepDive, Knowledge Vault

Will cover in "DI for ML"

# Distant Supervision [Mintz et al., ACL'09]

**Corpus Text**

Bill Gates founded Microsoft in 1975.
Bill Gates, founder of Microsoft, …
Bill Gates attended Harvard from …
Google was founded by Larry Page …

**Training Data**

**Freebase**

(Bill Gates, Founder, Microsoft)
(Larry Page, Founder, Google)
(Bill Gates, CollegeAttended, Harvard)

[Adapted example from Luke Zettlemoyer]

# Distant Supervision [Mintz et al., ACL'09]

**Corpus Text**

Bill Gates founded Microsoft in 1975.
Bill Gates, founder of Microsoft, …
Bill Gates attended Harvard from …
Google was founded by Larry Page …

**Training Data**

(Bill Gates, Microsoft)
Label: Founder
Feature: X founded Y

**Freebase**

(Bill Gates, Founder, Microsoft)
(Larry Page, Founder, Google)
(Bill Gates, CollegeAttended, Harvard)

[Adapted example from Luke Zettlemoyer]

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**Training Data**

(Bill Gates, Microsoft)
Label: Founder
Feature: X founded Y
Feature: X, founder of Y

**Freebase**

(Bill Gates, Founder, Microsoft)
(Larry Page, Founder, Google)
(Bill Gates, CollegeAttended, Harvard)

[Adapted example from Luke Zettlemoyer]

# Distant Supervision [Mintz et al., ACL’09]

**Corpus Text**

Bill Gates founded Microsoft in 1975.
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Bill Gates attended Harvard from …
Google was founded by Larry Page …

**Freebase**

(Bill Gates, Founder, Microsoft)
(Larry Page, Founder, Google)
(Bill Gates, CollegeAttended, Harvard)

**Training Data**

(Bill Gates, Microsoft)
Label: Founder
Feature: X founded Y
Feature: X, founder of Y

(Bill Gates, Harvard)
Label: CollegeAttended
Feature: X attended Y

For negative examples, sample unrelated pairs of entities.

[Adapted example from Luke Zettlemoyer]

# Label Generation for Extraction Training

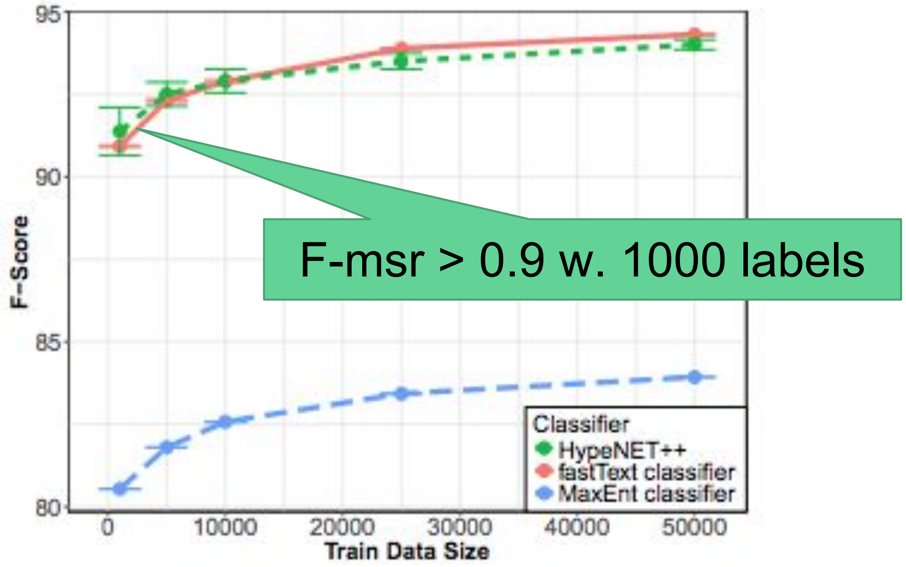
Where are training labels from?

**~2005 (Rel. Ex.)**

**Relation extraction from texts**

- NER→EL→RE
  - Feature based: LR, SVM
  - Kernel based: SVM
- Distant supervision
- OpenIE

- Distant supervision: HyperNet++
  [Christodoulopoulos & Mittal, 18]



# Label Generation for Extraction Training

Where are training labels from?

**2013 (Deep ML)**

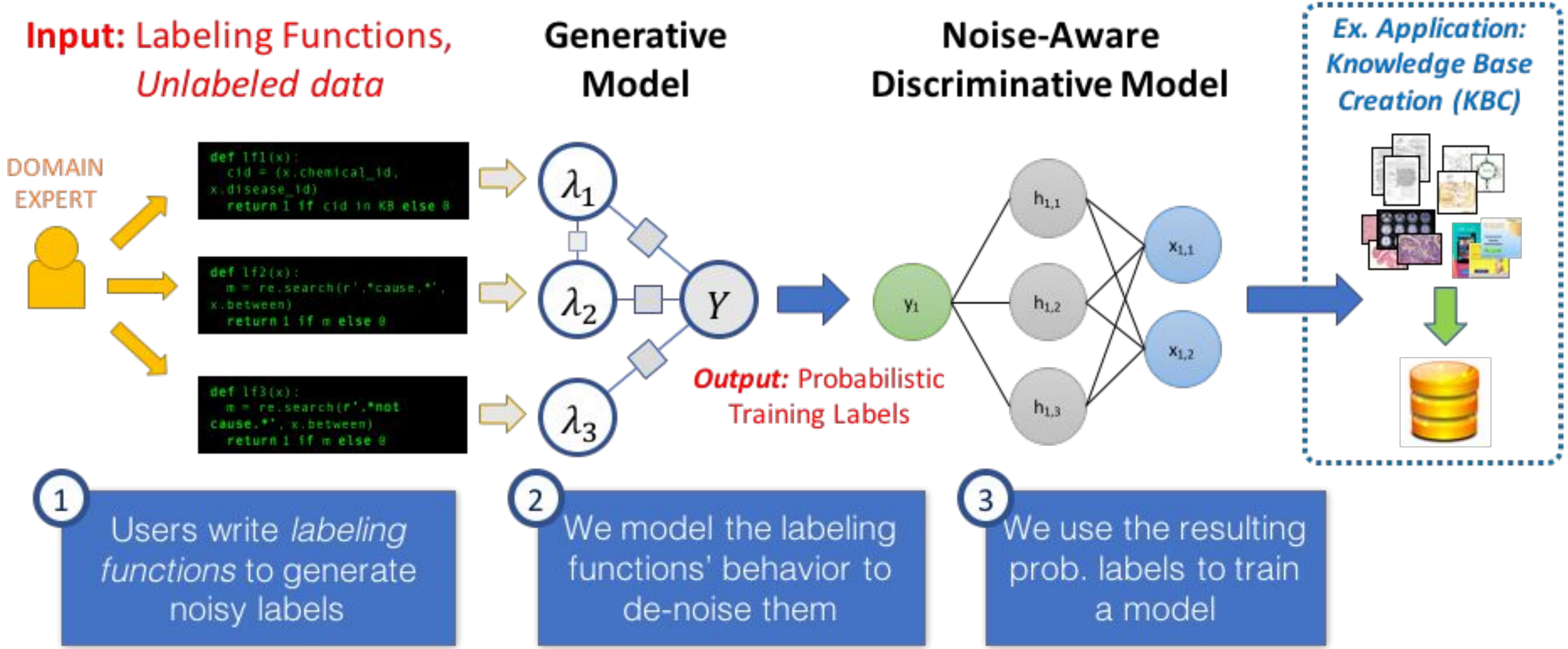
**Deep learning**

- Use RNN, CNN, attention for RE
- Data programming / Heterogeneous learning
- Revisit DOM extraction

Will cover in “DI for ML”

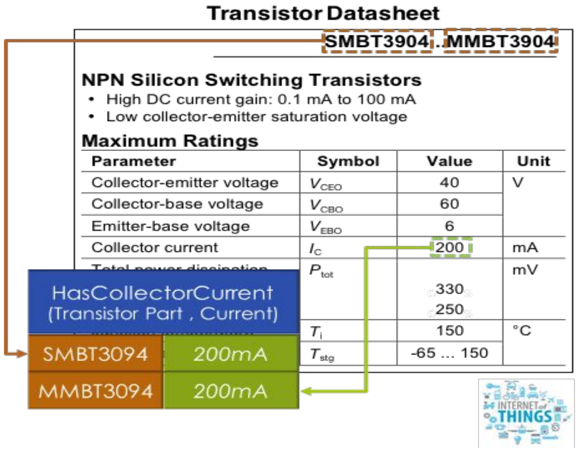
- **Semi-supervised learning**
  - Iterative extraction [Carlson et al., AAAI’10]
    Use new extractions to retrain models
    E.g., NELL
- **Weak learning**
  - Distant supervision [Mintz et al., ACL’09]
    Rule-based annotation with seed data
    E.g., DeepDive, Knowledge Vault
  - Data programming [Ratner et al., NIPS’16]
    Manually write labelling functions
    E.g., Snorkle, Fouduer

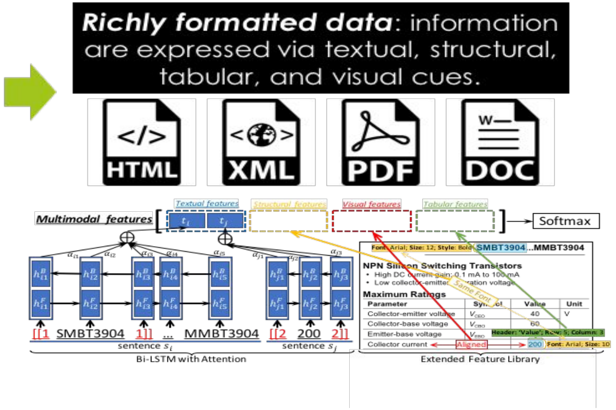
# Snorkel: Code as Supervision [Ratner et al., NIPS'16, VLDB'18]




[Slide by Alex Ratner]

# Example System: Fonduer [Wu et al., SIGMOD'18]




Fonduer combines a new **biLSTM with multimodal features** and **data programming**.

| System | ELEC. | GEN. | |
|---|---|---|---|
| Knowledge Base | Digi-Key | GWAS Central | GWAS Catalog |
| # Entries in KB | 376 | 3,008 | 4,023 |
| # Entries in Fonduer | 447 | 6,420 | 6,420 |
| Coverage | 0.99 | 0.82 | 0.80 |
| Accuracy | 0.87 | 0.87 | 0.89 |
| # New Correct Entries | 17 | 3,154 | 2,486 |
| Increase in Correct Entries | 1.05× | 1.87× | 1.42× |

New version of code coming soon: https://github.com/HazyResearch/fonduer

# OpenIE from Texts

~2005 (Rel. Ex.)

**Relation extraction from texts**

- NER→EL→RE
  - Feature based: LR, SVM
  - Kernel based: SVM
- Distant supervision
- OpenIE

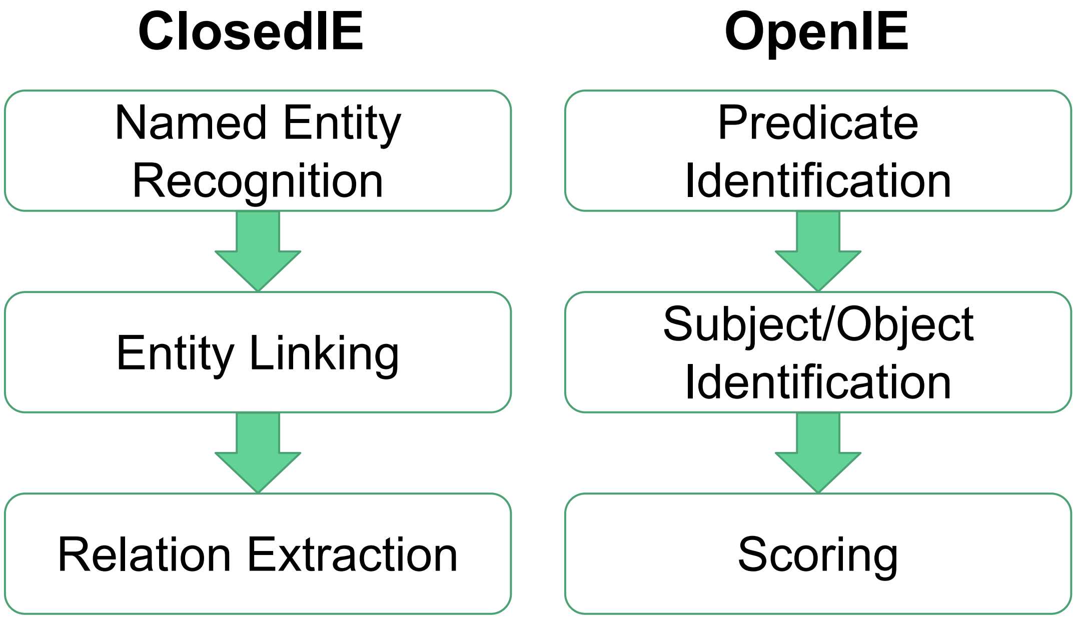
Where are predicates from?

- **ClosedIE**
  - Only extracting facts corresponding to ontology
  - Normalize predicates by ontology
  - E.g., (Bill Gates, /person/isFounder, Microsoft)

Bill Gates founded Microsoft in 1975.

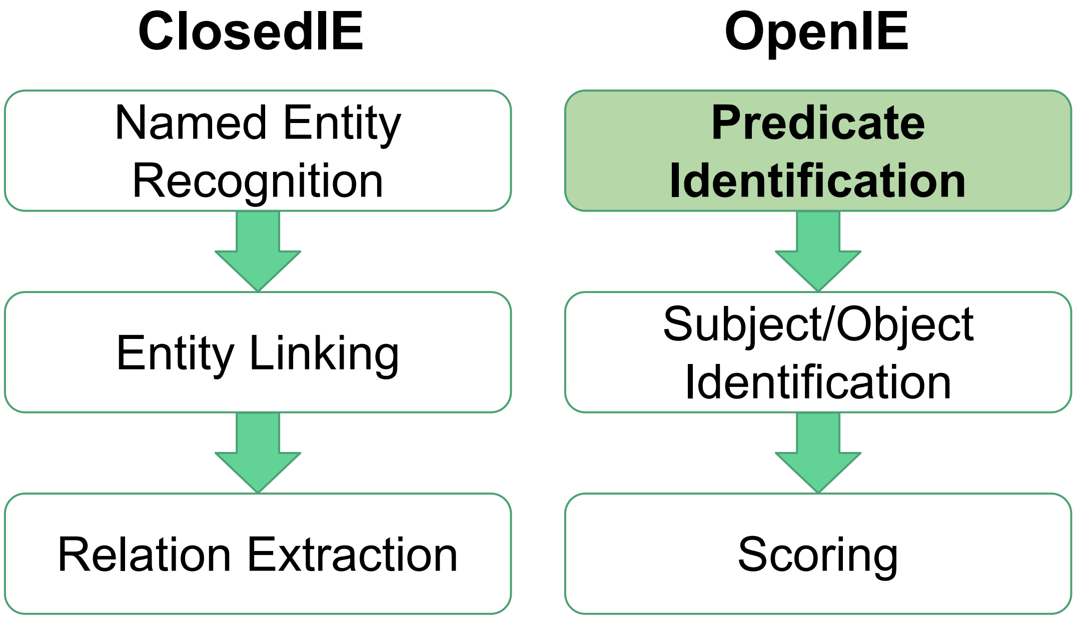
- **OpenIE** [Banko et al., IJCAI'07]
  - Extract all relations expressed in texts
  - Predicates are unnormalized strings
  - E.g., ("Bill Gates", "founded", "Microsoft")

# OpenIE from Texts [Etzioni et al., IJCAI'11]




Bill Gates founded Microsoft in 1975.

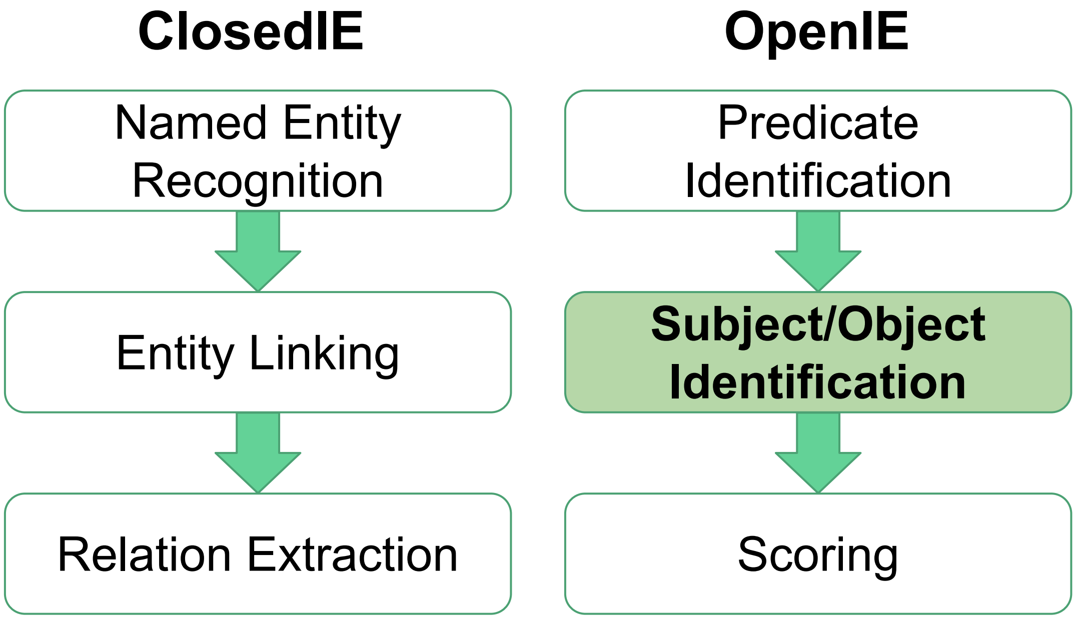
# OpenIE from Texts [Etzioni et al., IJCAI'11]




Bill Gates founded Microsoft in 1975.

- Predicate: longest sequence of words as light verb construction

# OpenIE from Texts [Etzioni et al., IJCAI'11]




Bill Gates founded Microsoft in 1975.

- Predicate: longest sequence of words as light verb construction
- Subject: learn left and right boundary
- Object: learn right boundary

# OpenIE from Texts [Etzioni et al., IJCAI'11]

**ClosedIE**

Named Entity Recognition

↓

Entity Linking

↓

Relation Extraction

**OpenIE**

Predicate Identification

↓

Subject/Object Identification

↓

**Scoring**

Bill Gates founded Microsoft in 1975.

- Predicate: longest sequence of words as light verb construction
- Subject: learn left and right boundary
- Object: learn right boundary
- LR for triple confidence

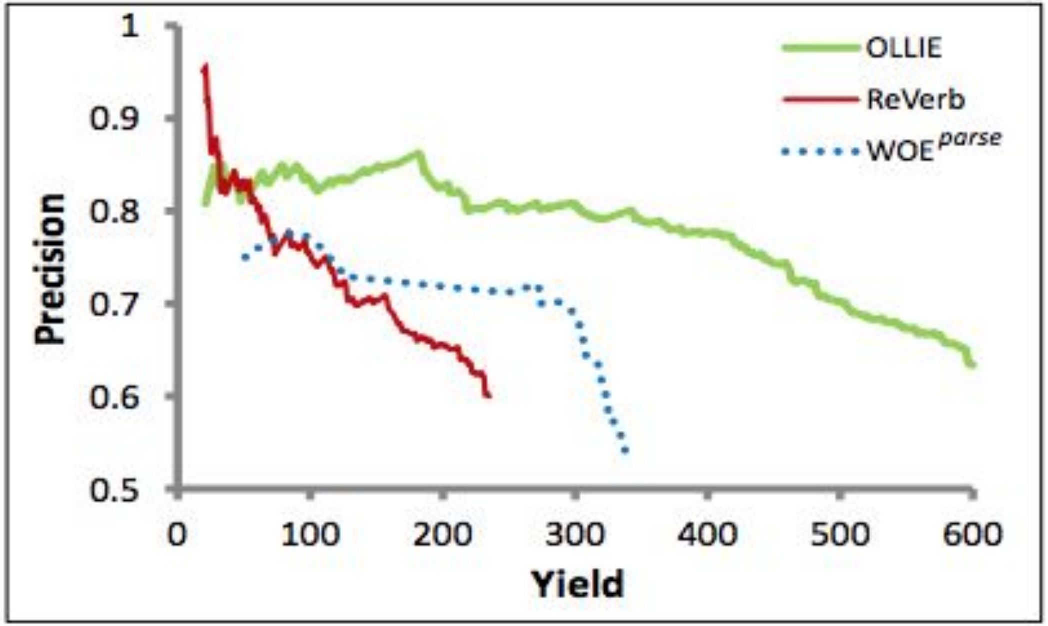
# OpenIE from Texts [Mausam et al., EMNLP'12]

Where are predicates from?

## ~2005 (Rel. Ex.)

**Relation extraction from texts**

- NER→EL→RE
  - Feature based: LR, SVM
  - Kernel based: SVM
- Distant supervision
- OpenIE



# Extraction from Semi-Structured Data

**Extraction from semi-structured data**

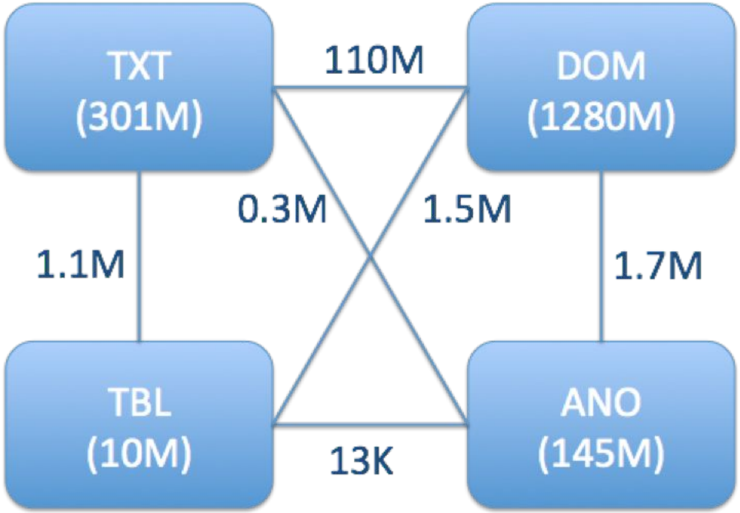
- WebTables: search, extraction
- DOM tree: wrapper induction

**2008 (Semi-stru)**

# Why Semi-Structured Data?

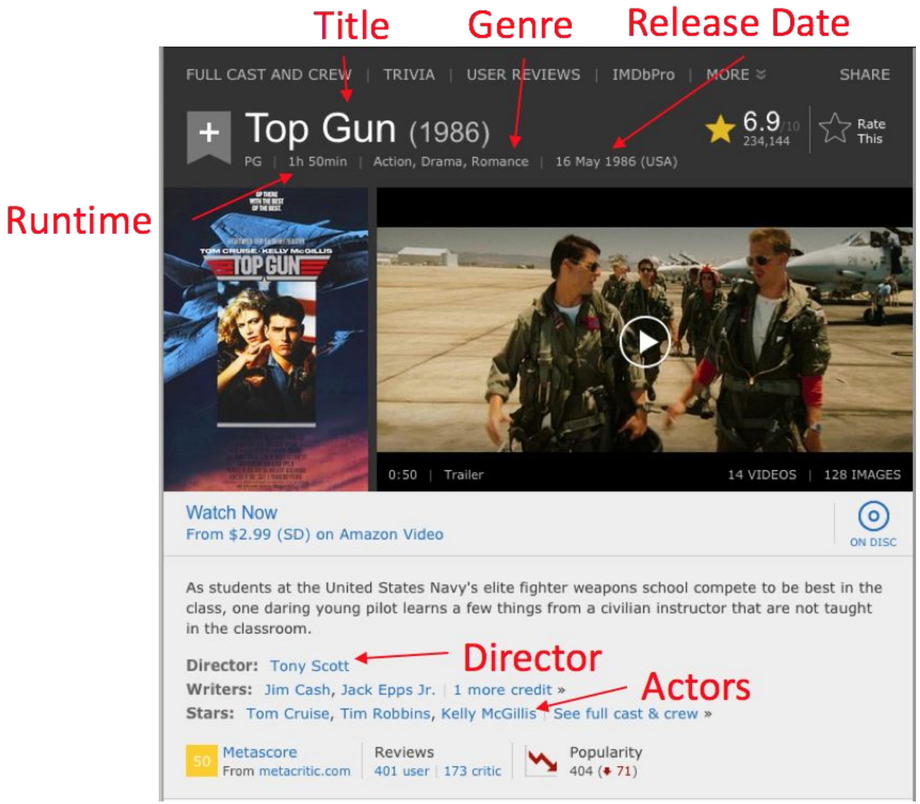
- Knowledge Vault @ Google showed big potential from DOM-tree extraction [Dong et al., KDD’14][Dong et al., VLDB’14]

| Accu | Accu (conf $\geq .7$) |
|---|---|
| 0.36 | 0.52 |




| Accu | Accu (conf $\geq .7$) |
|---|---|
| 0.43 | 0.63 |
| 0.09 | 0.62 |

# Wrapper Induction--Vertex [Gulhane et al., ICDE'11]




## Extracted relationships

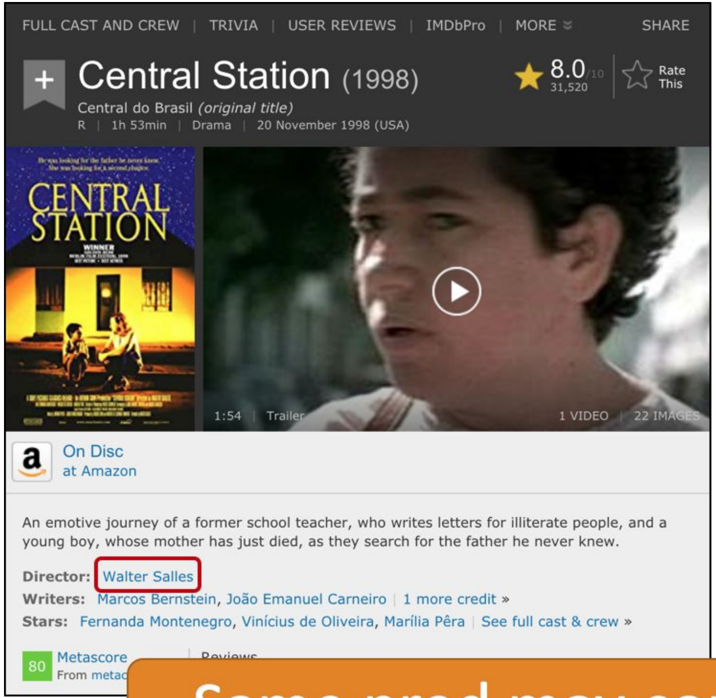
- (Top Gun, type.object.name, "Top Gun")
- (Top Gun, film.film.genre, Action)
- (Top Gun, film.film.directed_by, Tony Scott)
- (Top Gun, film.film.starring, Tom Cruise)
- (Top Gun, film.film.runtime, "1h 50min")
- (Top Gun, film.film.release_Date_s, "16 May 1986")

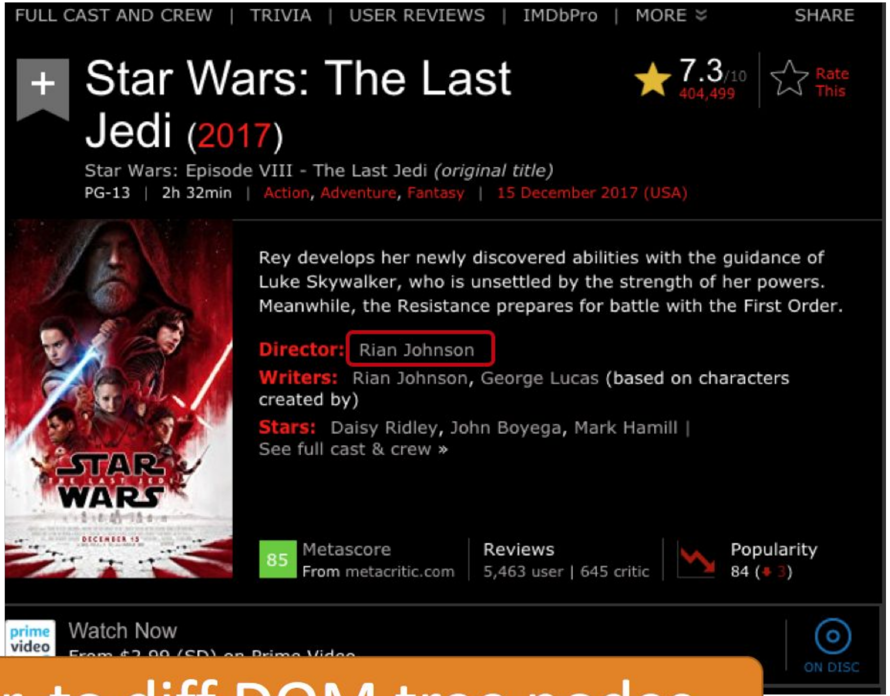
# Wrapper Induction--Vertex [Gulhane et al., ICDE'11]

- Solution: find XPaths from DOM Trees


# Wrapper Induction--Vertex [Gulhane et al., ICDE'11]

- Challenge: slight variations from page to page

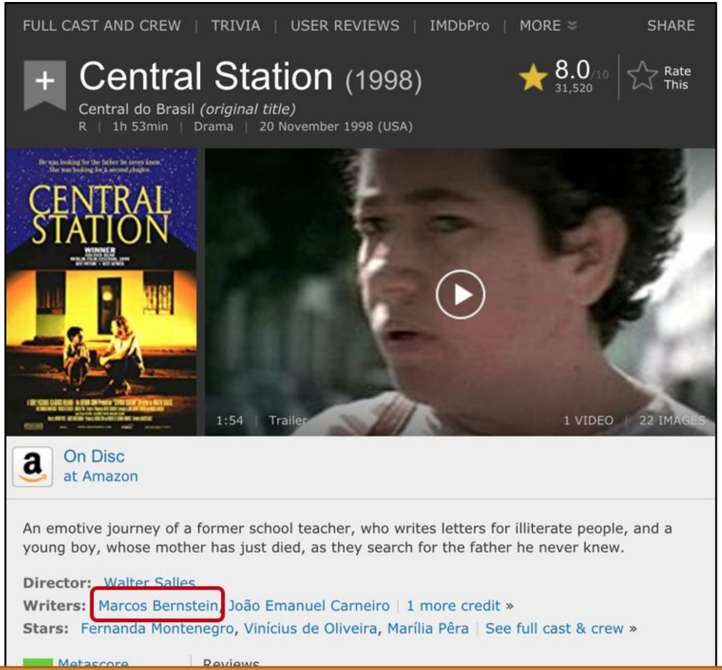


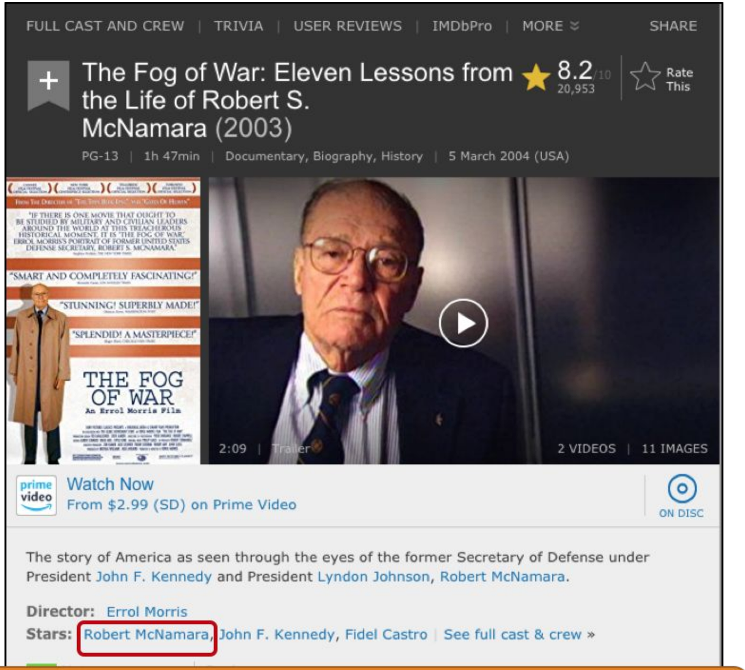




Same pred may corr. to diff DOM tree nodes

# Wrapper Induction--Vertex [Gulhane et al., ICDE'11]

- Challenge: slight variations from page to page



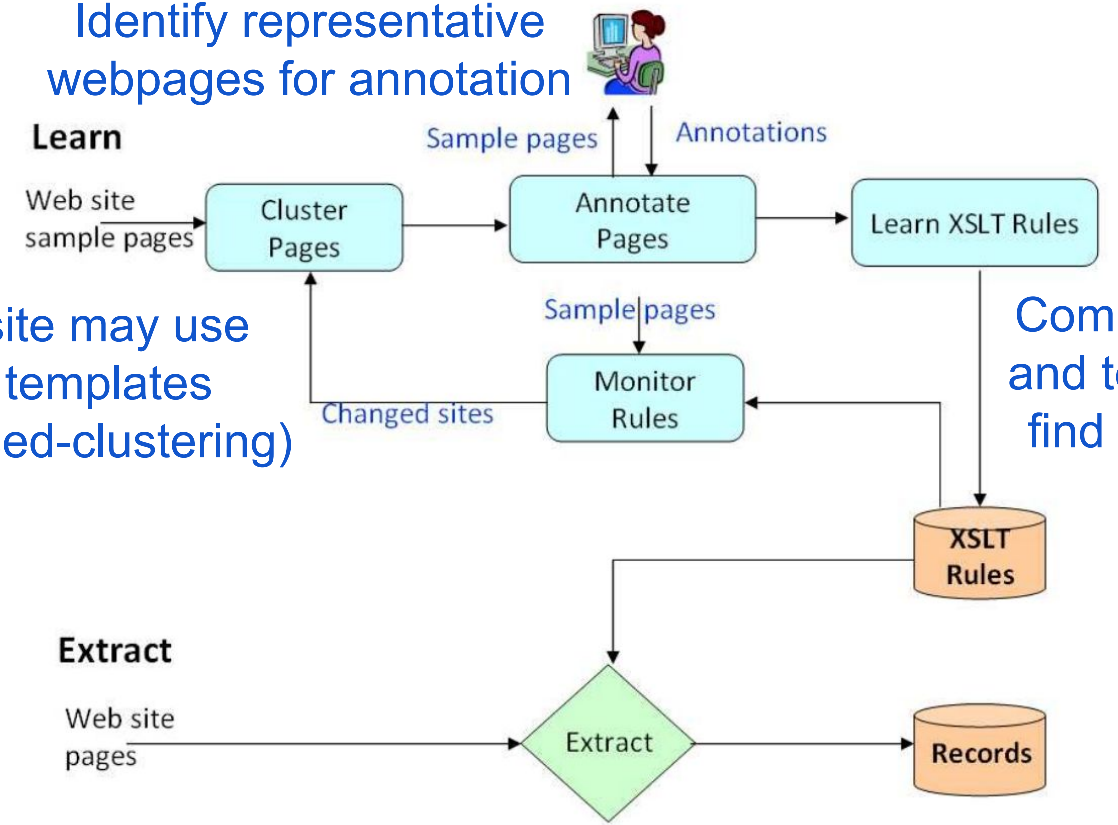

Same DOM tree node may correspond to diff preds

# Wrapper Induction--Vertex [Gulhane et al., ICDE’11]

Identify representative webpages for annotation

One website may use multiple templates (Unsupervised-clustering)

Combine attr features and textual features to find a general XPath (LR)



# Wrapper Induction--Vertex [Gulhane et al., ICDE’11]

- **Sample learned XPaths on IMDb**
  - //*[@itemprop="name"]
  - //*[@class="bp_item bp_text_only"]/*/*/*[@class="bp_heading"]
  - //*[following-sibling::*[position()=3][@class="subheading"]]/*[following-sibling::*[position()=1][@class="attribute"]]
  - //*[preceding-sibling::node()[normalize-space(.)!=""][text()="Language:"]

Ensure high recall

Ensure high precision

# Distantly Supervised Extraction

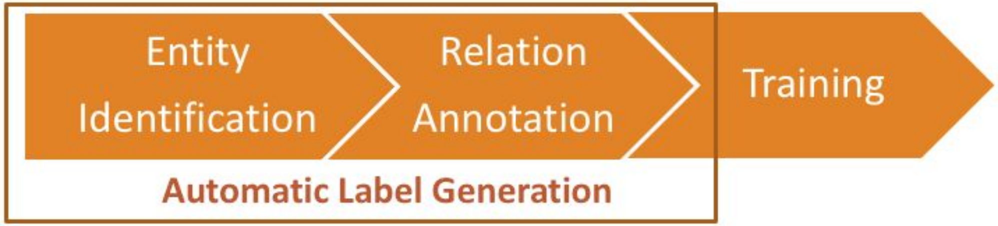
**2013 (Deep ML)**

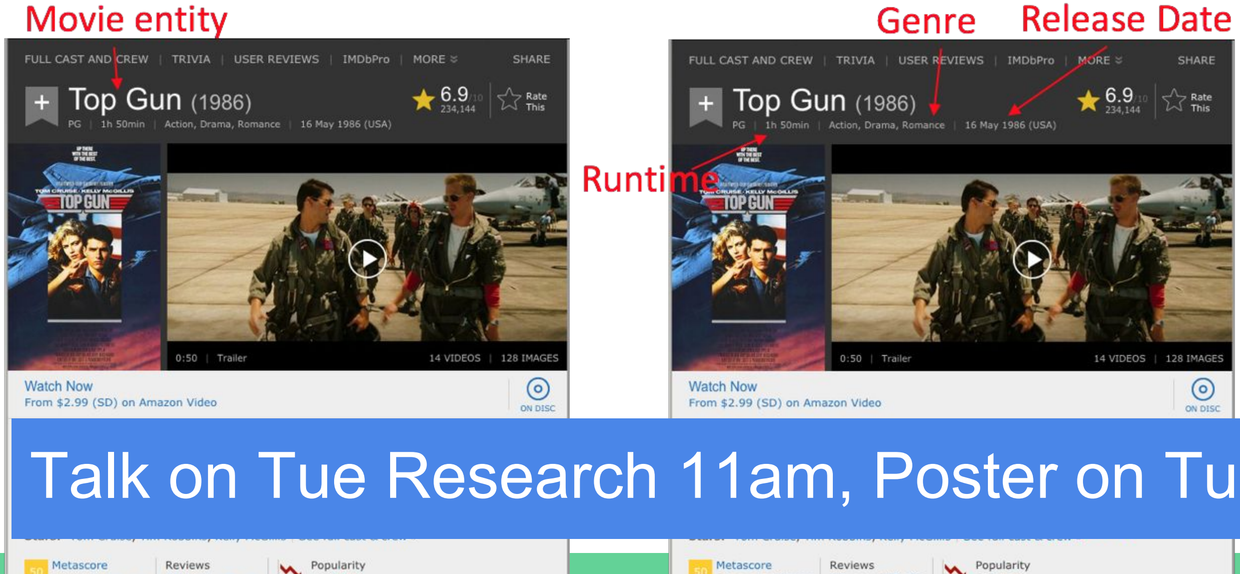
**Deep learning**

- Use RNN, CNN, attention for RE
- Data programming / Heterogeneous learning
- Revisit DOM extraction

- **Annotation-based extraction**
  - Pros: high precision and recall
  - Cons: does not scale--annotation per cluster per website
- **Distantly-supervised extraction**
  - Step 1. Use seed data to automatically annotate
  - Step 2. Use the (noisy) annotations for training
  - E.g., DeepDive, Knowledge Vault

# Distantly Supervised Extraction--Ceres [Lockard et al., VLDB'18]




Extracted triples

- (Top Gun, type.object.name, "Top Gun")
- (Top Gun, film.film.genre, Action)
- (Top Gun, film.film.directed_by, Tony Scott)
- (Top Gun, film.film.starring, Tom Cruise)
- (Top Gun, film.film.runtime, "1h 50min")
- (Top Gun, film.film.release_Date_s, "16 May 1986")

Talk on Tue Research 11am, Poster on Tue Posters I 17:30pm

# Distantly Supervised Extraction--Ceres [Lockard et al., VLDB'18]

- Extraction experiments on SWDE benchmark

| Vertical | Predicate | Vertex++ | | | CERES-Full | | |
|---|---|---|---|---|---|---|---|
| | | P | R | F1 | P | R | F1 |
| Movie | Title | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | Director | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 |
| | Genre | 0.88 | 0.87 | 0.87 | **0.93** | **0.97** | **0.95** |
| | MPAA Rating | 1.00 | 1.00 | 1.00 | NA | NA | NA |
| | Average | 0.97 | 0.97 | 0.97 | 0.97 | **0.99** | **0.98** |
| NBAPlayer | Name | 0.99 | 0.99 | 0.99 | **1.00** | **1.00** | **1.00** |
| | Team | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.95 |
| | Weight | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | Height | 1.00 | 1.00 | 1.00 | 1.00 | 0.90 | 0.95 |
| | Average | 1.00 | 1.00 | 1.00 | 0.98 | 0.98 | 0.98 |

| Vertical | Predicate | Vertex++ | | | CERES-Full | | |
|---|---|---|---|---|---|---|---|
| | | P | R | F1 | P | R | F1 |
| University | Name | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | Type | 1.00 | 1.00 | 1.00 | 0.72 | 0.80 | 0.76 |
| | Phone | 0.97 | 0.92 | 0.94 | 0.85 | **0.95** | 0.90 |
| | Website | 1.00 | 1.00 | 1.00 | 0.90 | 1.00 | 0.95 |
| | Average | 0.99 | 0.98 | 0.99 | 0.87 | 0.94 | 0.90 |
| Book | Title | 0.99 | 0.99 | 0.99 | **1.00** | 0.90 | 0.95 |
| | Author | 0.97 | 0.96 | 0.96 | 0.72 | 0.88 | 0.79 |
| | Publisher | 0.85 | 0.85 | 0.85 | **0.97** | 0.77 | **0.86** |
| | Publication Date | 0.90 | 0.90 | 0.90 | **1.00** | 0.40 | 0.57 |
| | ISBN-13 | 0.94 | 0.94 | 0.94 | **0.99** | 0.19 | 0.32 |
| | Average | 0.93 | 0.93 | 0.93 | **0.94** | 0.63 | 0.70 |

Very high precision

Competent w. Wrapper induction w. manual annotation

# Distantly Supervised Extraction--Ceres [Lockard et al., VLDB'18]

- Extraction on long-tail movie websites

| #Websites / #Webpages | 33 / 434K |
|---|---|
| Language | English and 6 other languages |
| Domains | Animated films, Documentary films, Financial performance, etc. |
| # Annotated pages | 70K (16%) |
| Annotated : Extracted #entities | 1 : **2.6** |
| Annotated : Extracted #triples | 1 : **3.0** |
| # Extractions | 1.25 M |
| Precision | 90% |

# Distantly Supervised Extraction--Ceres [Lockard et al., VLDB'18]

**2013 (Deep ML)**

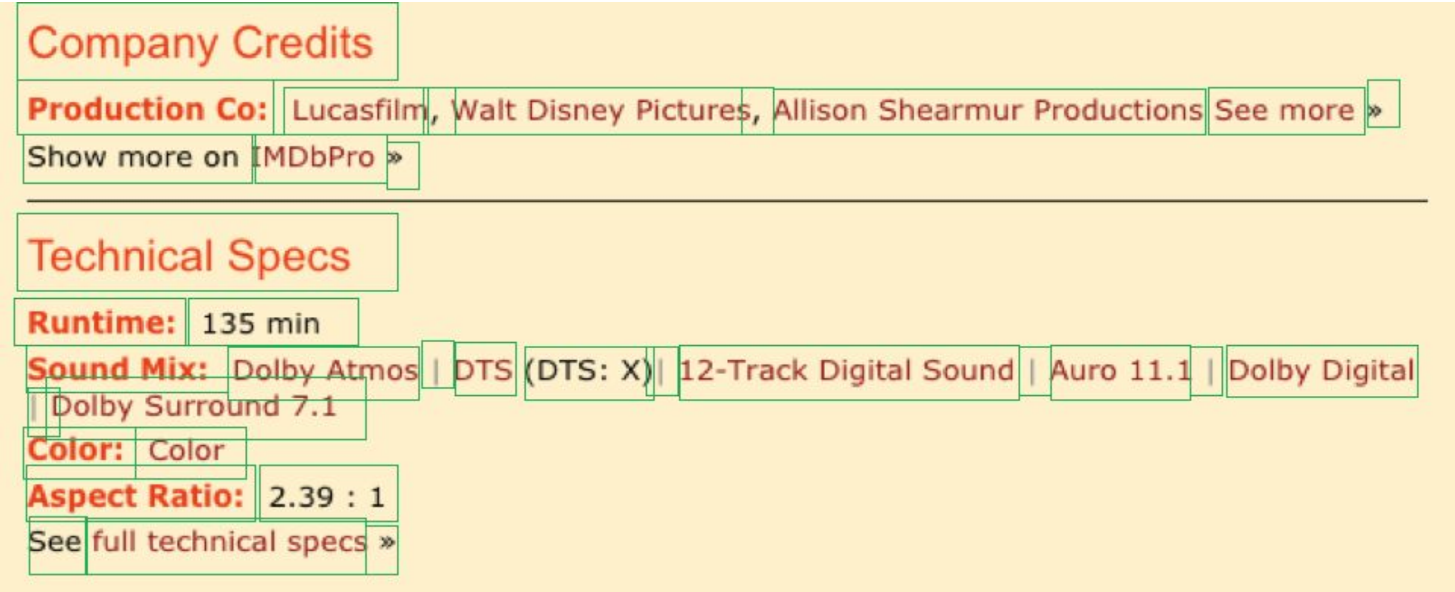
**Deep learning**

- Use RNN, CNN, attention for RE
- Data programming / Heterogeneous learning
- Revisit DOM extraction

- **Which model is the best?**
  - Logistic regression: best results (20K features on one website)
  - Random forest: lower precision and recall
  - Deep learning??

# Challenges in Applying Deep Learning on Extracting Semi-structured Data

- Web layout is neither 1D sequence nor regular 2D grid, so CNN or RNN does not directly apply



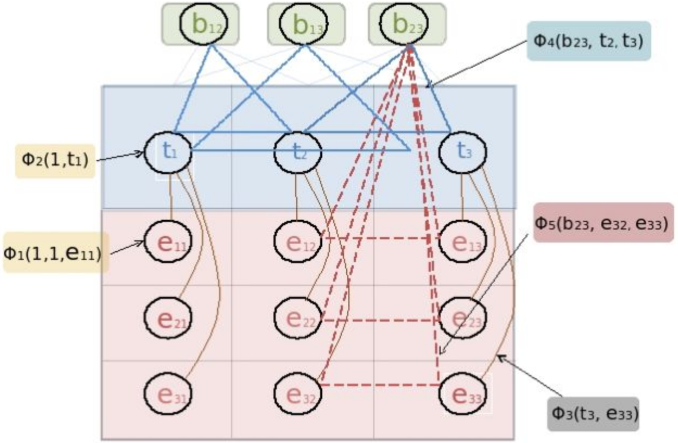
# WebTable Extraction [Limaye et al., VLDB'10]

- Model table annotation using interrelated random variables, represented by a probabilistic graphical model
  - Cell text (in Web table) and entity label (in catalog)
  - Column header (in Web table) and type label (in catalog)
  - Column type and cell entity (in Web table)

**Extraction from semi-structured data**

- WebTables: search, extraction
- DOM tree: wrapper induction

**2008 (Semi-stru)**




**Check-out 10-Year Best Paper Award for WebTable *Search* on Thursday!**

# WebTable Extraction [Limaye et al., VLDB'10]

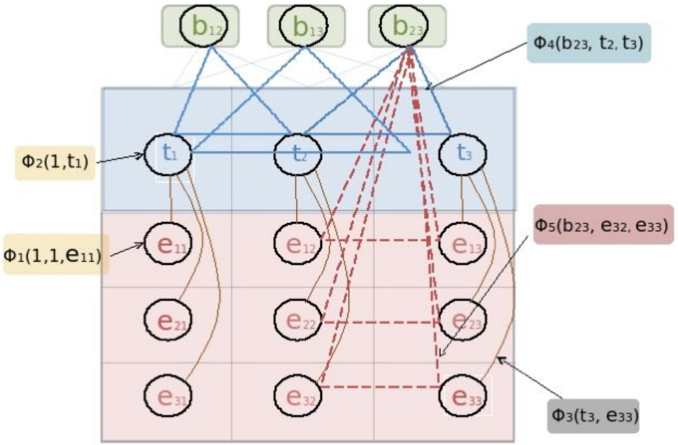
- Model table annotation using interrelated random variables, represented by a probabilistic graphical model
  - Pair of column types (in Web table) and relation (in catalog)
  - Entity pairs (in Web table) and relation (in catalog)

**Extraction from semi-structured data**

- WebTables: search, extraction
- DOM tree: wrapper induction

**2008 (Semi-stru)**

**Check-out 10-Year Best Paper Award for WebTable *Search* on Thursday!**



# Challenges in Applying ML on DX

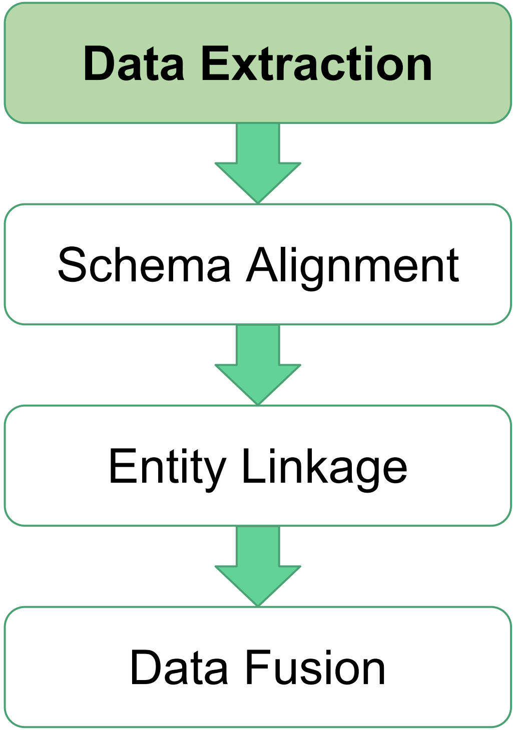
- Automatic data extraction cannot reach production quality requirement. How to improve precision?

- Every web designer has her own whim, but there are underlying patterns across websites. How to learn extraction patterns on different websites, especially for semi-structured sources?

- ClosedIE throws away too much data. How to apply OpenIE on all kinds of data?

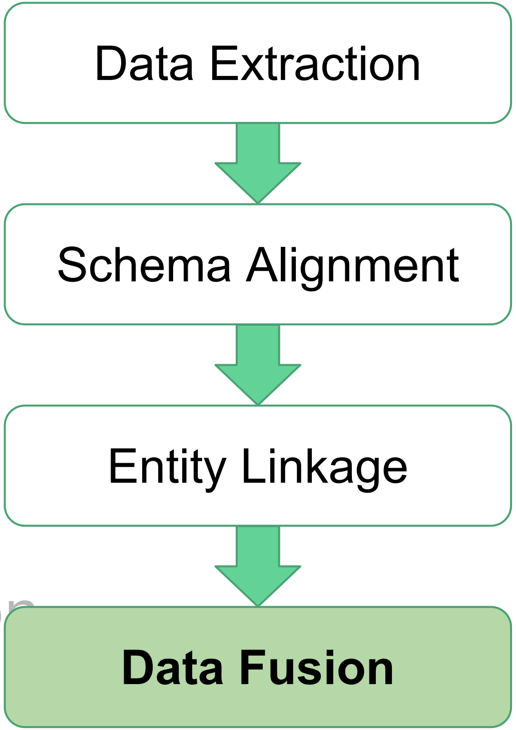
# Recipe for Data Extraction

- Problem definition: **Extract structure from semi- or un-structured data**
- Short answers
  - **Wrapper induction has high prec/rec**
  - **Distant supervision is critical for collecting training data**
  - **DL effective for texts and LR is often effective for semi-stru data**

# Outline

- Part I. Introduction
- Part II. ML for DI
  - ML for entity linkage
  - ML for data extraction
  - ML for data fusion
  - ML for schema alignment
- Part III. DI for ML
- Part IV. Conclusions and research directio



# What is Data Fusion?

- **Definition:** Resolving conflicting data and verifying facts.
- **Example:** “*OK Google,How long is the Mississippi River?*”

Mississippi River / Length

2,320 mi

People also search for


Missouri River
2.341K mi


Nile
4.258K mi

## Mississippi River

River in the United States of America

4.2 ★★★★★ 400 Google reviews

The Mississippi River is the chief river of the second-largest drainage system on the North American continent, second only to the Hudson Bay drainage system. Wikipedia

**Discharge:** 593,000 cubic feet per second

**Basin area:** 1.151 million mi²

**Source:** Lake Itasca

**Mouth:** Gulf of Mexico

**Country:** United States of America

**Did you know:** The Mississippi River is the second-longest river in the US (2,202 mi). wikipedia.org

Mississippi River Facts - Mississippi National River and Recreation ...

https://www.nps.gov/miss/riverfacts.htm

Nov 14, 2017 - The staff of Itasca State Park at the Mississippi's headwaters suggest the main stem of the river is **2,552 miles** long. The US Geologic Survey has published a number of **2,300 miles**, the EPA says it is **2,320 miles** long, and the Mississippi National River and Recreation Area suggests the river's length is **2,350 miles**.

| # | Name | Mouth[5] | Length | Source coordinates[11] | Mouth coordinates[11] | Watershed area[12] | Discharge[12] | States, provinces, and image[5][11] |
|---|---|---|---|---|---|---|---|---|
| 1 | Missouri River | Mississippi River | 2,341 mi 3,768 km[13] | 45°55′39″N 111°30′29″W[14] | 38°48′49″N 90°07′11″W | 529,353 mi² 1,371,017 km²[15] ‡[n 2] | 69,100 ft³/s 1,956 m³/s [n 3] | Montana[s], North Dakota, South Dakota, Nebraska, Iowa, Kansas, Missouri[m]  |
| 2 | Mississippi River | Gulf of Mexico | 2,202 mi 3,544 km[17] [n 4] | 47°14′22″N 95°12′29″W[18] | 29°09′04″N 89°15′12″W | 1,260,000 mi² 3,270,000 km²[19] ‡[n 5] | 650,000 ft³/s 18,400 m³/s | Minnesota[s], Wisconsin, Iowa, Illinois, Missouri, Kentucky, Tennessee, Arkansas, Mississippi, Louisiana[m]  |

# The Basic Setup of Data Fusion

### Source Observations

| Source | River | Attribute | Value |
|---|---|---|---|
| KG | Mississippi River | Length | 2,320 mi |
| KG | Missouri River | Length | 2,341 mi |
| Wikipedia | Mississippi River | Length | 2,202 mi |
| Wikipedia | Missouri River | Length | 2,341 mi |
| USGS | Mississippi River | Length | 2,340 mi |
| USGS | Missouri River | Length | 2,540 mi |

Fact

Conflicting value

Source reports a value for a fact

### True Facts

| River | Attribute | Value |
|---|---|---|
| Mississippi River | Length | ? |
| Missouri River | Length | ? |

Fact's true value

**Goal:** Find the **latent** true value of facts.

# The Basic Setup of Data Fusion

Source Observations

| Source | River | Attribute | Value |
|---|---|---|---|
| KG | Mississippi River | Length | 2,320 mi |
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Fact

Conflicting value

Source reports a value for a fact

True Facts

| River | Attribute | Value |
|---|---|---|
| Mississippi River | Length | ? |
| Missouri River | Length | ? |

Fact's true value

**Idea:** Use *redundancy* to infer the true value of each fact.

# Majority Voting for Data Fusion

Source Observations

| Source | River | Attribute | Value |
|---|---|---|---|
| KG | Mississippi River | Length | 2,320 mi |
| KG | Missouri River | Length | 2,341 mi |
| Wikipedia | Mississippi River | Length | 2,202 mi |
| Wikipedia | Missouri River | Length | 2,341 mi |
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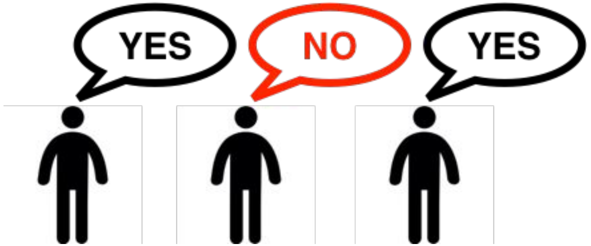
True Facts

| River | Attribute | Value |
|---|---|---|
| Mississippi River | Length | ? |
| Missouri River | Length | 2,341 |




Majority voting can be limited. What if sources are correlated (e.g., copying)?

**Idea:** Model source quality for accurate results.

MV's assumptions

1. Sources report values independently
2. Sources are better than chance.

# 40 Years of Data Fusion (beyond Majority Voting)

**1979 (Statistical learning)**

**Dawid-Skene model**
- Model the error-rate of sources
- Expectation-maximization

**~1996 (Rule-based)**

**Domain-specific Strategies**
- Keep all values
- Pick a random value
- Take the average value
- Take the most recent value
- ...

**2007 (Probabilistic)**

**Probabilistic Graphical Models**
- Use of generative models
- Focus on unsupervised learning

**2016 (Deep ML)**

**Deep learning**
- Use Restricted Boltzmann Machine; one layer version is equivalent with Dawid-Skene model
- Knowledge graph embeddings

# A Probabilistic Model for Data Fusion

- **Random variables:** Introduce a *latent random variable* to represent the true value of each fact.
- **Features:** Source observations become features associated with different random variables.
- **Model parameters:** Weights related to the error-rates of each data source.

error-rate scores (model parameters)

$$P(\text{Fact} = v|\text{data}) = \frac{1}{Z} \exp \sum_{s\ \in\ \text{Sources}} \sum_{v'\ \in\ \text{Values}} \sigma_S^{v,v'} \cdot 1[S \text{ reports Fact} = v']$$

Normalizing constant

$$\sigma_S^{v,v'} = \log\left(\frac{\text{Error-rate of Source } S}{1 - \text{Error-rate of Source } S}\right)$$

**Error-rate** = probability that a source provides value *v′* instead of value *v*

# The Challenge of Training Data

- How much data do we need to train the data fusion model?
- **Theorem:** We need a number of labeled examples proportional to the number of sources [Ng and Jordan, NIPS'01]
- **Model parameters:** Weights related to the error-rates of each data source.

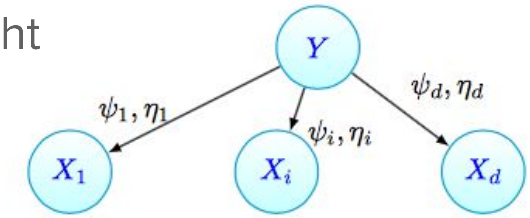
But the number of sources can be in the thousands or millions and training data is limited!

**Idea 1:** Leverage redundancy and use unsupervised learning.

# The Dawid-Skene Algorithm [Dawid and Skene, 1979]

Iterative process to estimate data source error rates

1. Initialize "inferred" true value for each fact (e.g., use majority vote)
2. Estimate **error rates** for workers (using "inferred" true values)
3. Estimate **"inferred" true values** (using error rates, weight source votes according to quality)
4. Go to Step 2 and iterate until convergence




**Assumptions:** (1) average source error rate < 0.5, (2) dense source observations, (3) conditional independence of sources, (4) errors are uniformly distributed across all instances.

# An Intro in Probabilistic Graphical Models

Bayesian Networks (BNs)

**Local Markov Assumption:** A variable X is independent of its non-descendants given its parents (and *only* its parents).

# An Intro in Probabilistic Graphical Models

Bayesian Networks (BNs)

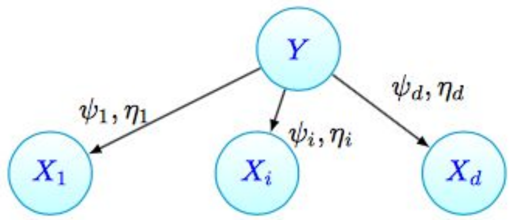
**Local Markov Assumption:** A variable X is independent of its non-descendants given its parents (and *only* its parents).

Recipe for BNs

Set of random variables X

Directed acyclic graph (each X[i] is a vertex)

Conditional probability tables P(X | Parents(X))



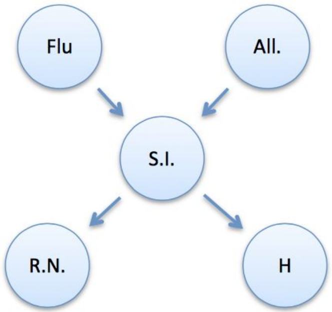

Joint distribution: Factorizes over conditional probability tables

# An Intro in Probabilistic Graphical Models

Where do independence assumptions come from?

**Causal structure** captures domain knowledge

- The flu causes sinus inflammation
- Allergies *also* cause sinus inflammation
- Sinus inflammation causes a runny nose
- Sinus inflammation causes headaches

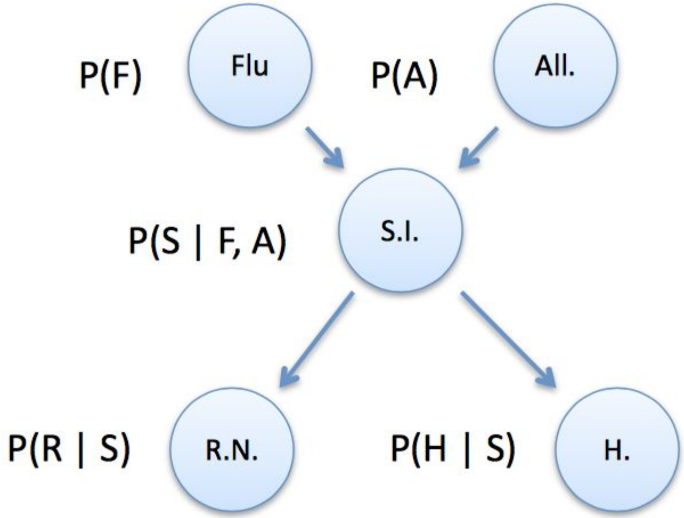



[Example by Andrew McCallum]

# An Intro in Probabilistic Graphical Models

Factored joint distribution

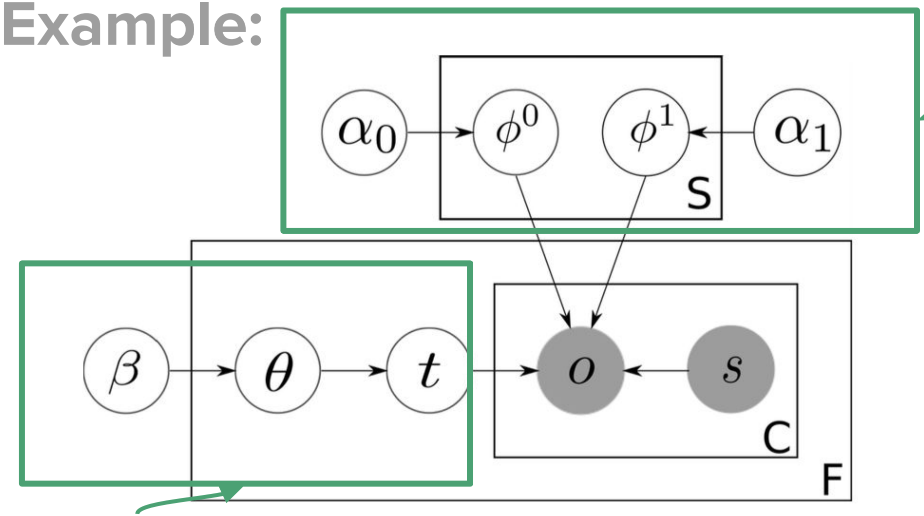
$$
\begin{aligned}
& P(F, A, S, R, H) \\
&= P(F) \\
&\quad P(A) \\
&\quad P(S \mid F, A) \\
&\quad P(R \mid S) \\
&\quad P(H \mid S)
\end{aligned}
$$




[Example by Andrew McCallum]

# Probabilistic Graphical Models for Data Fusion

**Example:**




Source Quality

Prior truth probability

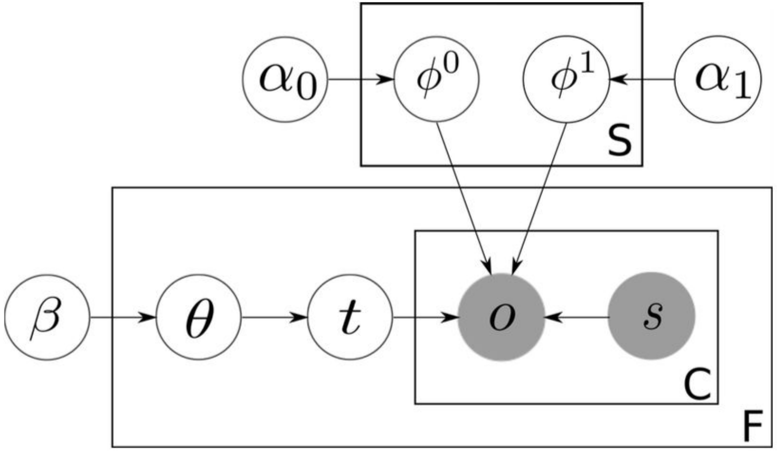
[Zhao et al., VLDB 2012]

**Setup: Identify true source claims**

| *Entity (Movie)* | *Attribute (Cast)* | *Source* |
|---|---|---|
| Harry Potter | Daniel Radcliffe | IMDB |
| Harry Potter | Emma Waston | IMDB |
| Harry Potter | Rupert Grint | IMDB |
| Harry Potter | Daniel Radcliffe | Netflix |
| Harry Potter | Daniel Radcliffe | BadSource.com |
| Harry Potter | Emma Waston | BadSource.com |
| Harry Potter | Johnny Depp | BadSource.com |
| Pirates 4 | Johnny Depp | Hulu.com |
| ... | ... | ... |

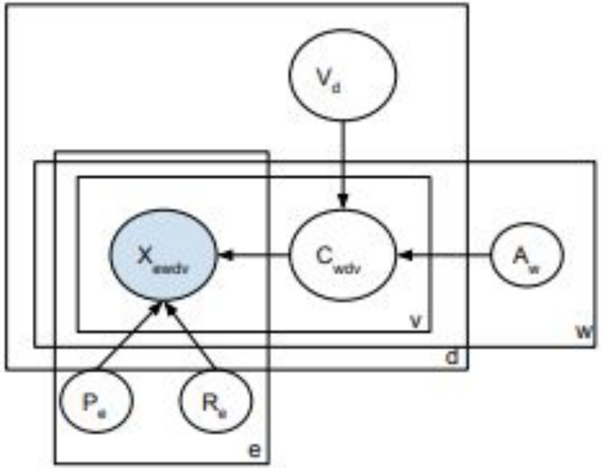
Extensive work on modeling source observations and source interactions to address limitations of basic Dawid-Skene.

# Probabilistic Graphical Models for Data Fusion




[Zhao et al., VLDB 2012]

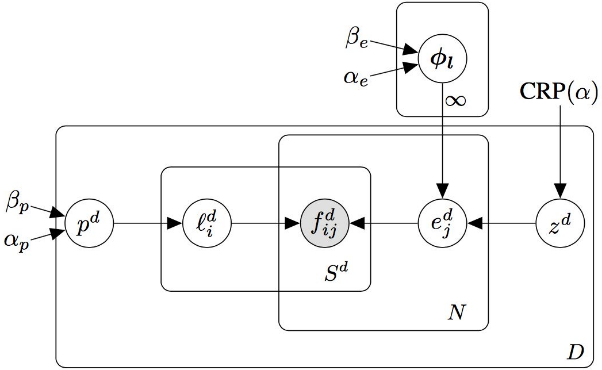
## Modeling both source quality and extractor accuracy



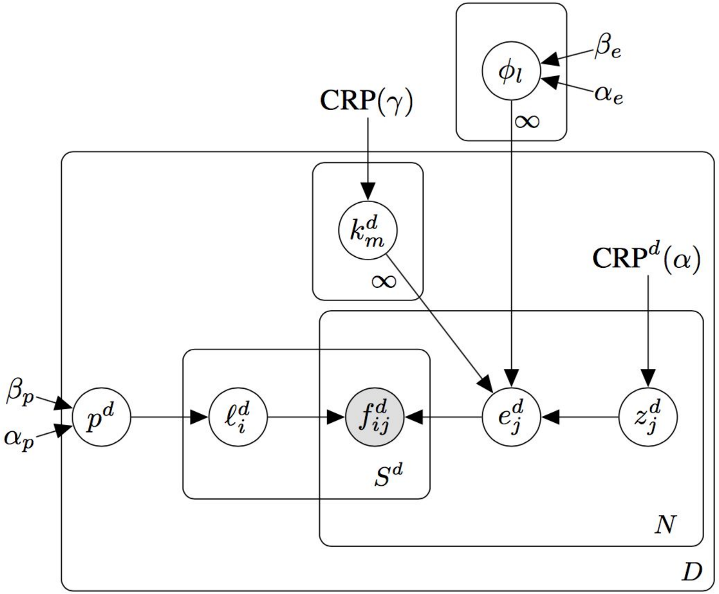

[Dong et al., VLDB 2015]

Extensive work on modeling source observations and source interactions to address limitations of basic Dawid-Skene.

# Probabilistic Graphical Models for Data Fusion




**Modeling source dependencies**




[Platanios et al., ICML 2016]

Extensive work on modeling source observations and source interactions to address limitations of basic Dawid-Skene.

# PGMs in Data Fusion [Li et al., VLDB'14]

**Table 6: Summary of data-fusion methods. X indicates that the method considers the particular evidence.**

| Category | Method | #Providers | Source trustworthiness | Item trustworthiness | Value Popularity | Value similarity | Value formatting | Copying |
|---|---|---|---|---|---|---|---|---|
| Baseline | Vote | X | | | | | | |
| Web-link based | HUB | X | X | | | | | |
| | AvgLog | X | X | | | | | |
| | Invest | X | X | | | | | |
| | PooledInvest | X | X | | | | | |
| IR based | 2-Estimates | X | X | | | | | |
| | 3-Estimates | X | X | X | | | | |
| | Cosine | X | X | | | | | |
| Bayesian based | TruthFinder | X | X | | | X | | |
| | AccuPr | X | X | | | | | |
| | PopAccu | X | X | | X | | | |
| | AccuSim | X | X | | | X | | |
| | AccuFormat | X | X | | | X | X | |
| Copying affected | AccuCopy | X | X | | | X | X | X |

Bayesian models capture source observations and source interactions.

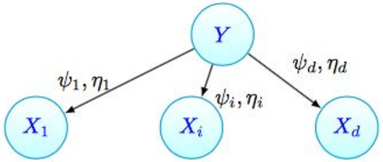
# PGMs in Data Fusion [Li et al., VLDB'14]

| Category | Method | Stock prec w. trust | Stock prec w/o. trust | Stock Trust dev | Stock Trust diff | Flight prec w. trust | Flight prec w/o. trust | Flight Trust dev | Flight Trust diff |
|---|---|---|---|---|---|---|---|---|---|
| Baseline | Vote | - | .908 | - | - | - | .864 | - | - |
| Web-link based | HUB | .913 | .907 | .11 | .08 | .939 | .857 | .2 | .14 |
| | AVGLOG | .910 | .899 | .17 | -.13 | .919 | .839 | .24 | .001 |
| | INVEST | .924 | .764 | .39 | -.31 | .945 | .754 | .29 | -.12 |
| | POOLEDINVEST | .924 | .856 | 1.29 | 0.29 | .945 | ***.921*** | 17.26 | 7.45 |
| IR based | 2-ESTIMATES | .910 | .903 | .15 | -.14 | .87 | .754 | .46 | -.35 |
| | 3-ESTIMATES | .910 | .905 | .16 | -.15 | .87 | .708 | .95 | -.94 |
| | COSINE | .910 | .900 | .21 | -.17 | .87 | .791 | .48 | -.41 |
| Bayesian based | TRUTHFINDER | .923 | .911 | .15 | .12 | ***.957*** | .793 | .25 | .16 |
| | ACCUPR | .910 | .899 | .14 | -.11 | .91 | .868 | .16 | -.06 |
| | POPACCU | .909 | .892 | .14 | -.11 | ***.958*** | ***.925*** | .17 | -.11 |
| | ACCUSIM | .918 | ***.913*** | .17 | -.16 | .903 | .844 | .2 | -.09 |
| | ACCUFORMAT | .918 | .911 | .17 | -.16 | .903 | .844 | .2 | -.09 |
| | ACCUSIMATTR | ***.950*** | ***.929*** | .17 | -.16 | .952 | .833 | .19 | -.08 |
| | ACCUFORMATATTR | ***.948*** | **.930** | .17 | -.16 | .952 | .833 | .19 | -.08 |
| Copying affected | ACCUCOPY | **.958** | .892 | .28 | -.11 | **.960** | **.943** | .16 | -.14 |

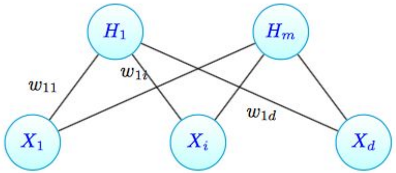
Modeling the quality of data sources leads to improved accuracy.

# Dawid-Skene and Deep Learning [Shaham et al., ICML'16]

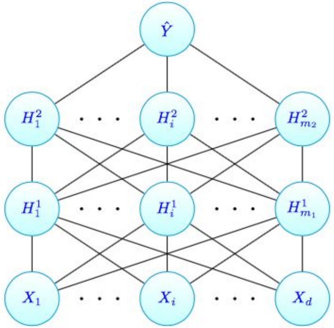
**Theorem:** The Dawid and Skene model is *equivalent* to a Restricted Boltzmann Machine (RBM) with a single hidden node.




**Dawid and Skene model.**



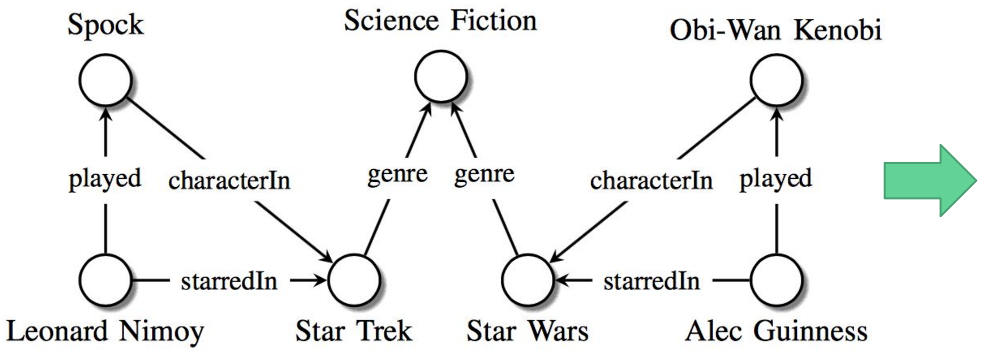

**A RBM with *d* visible and *m* hidden units.**

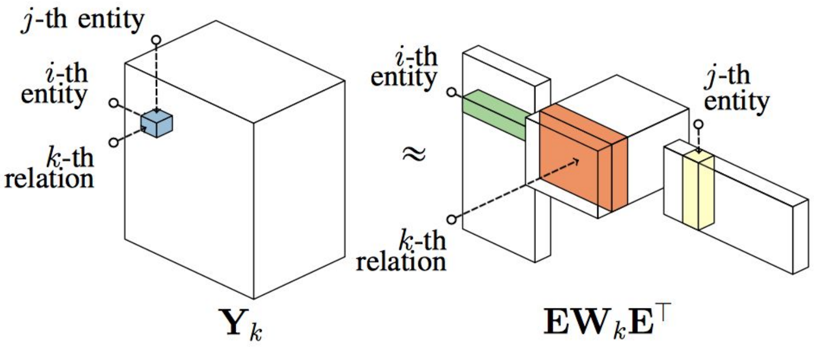



**Sketch of a two-hidden-layer RBM-based DNN.**

When the conditional independence assumption of Dawid-Skene does not hold, a better approximation may be obtained from a deeper network.

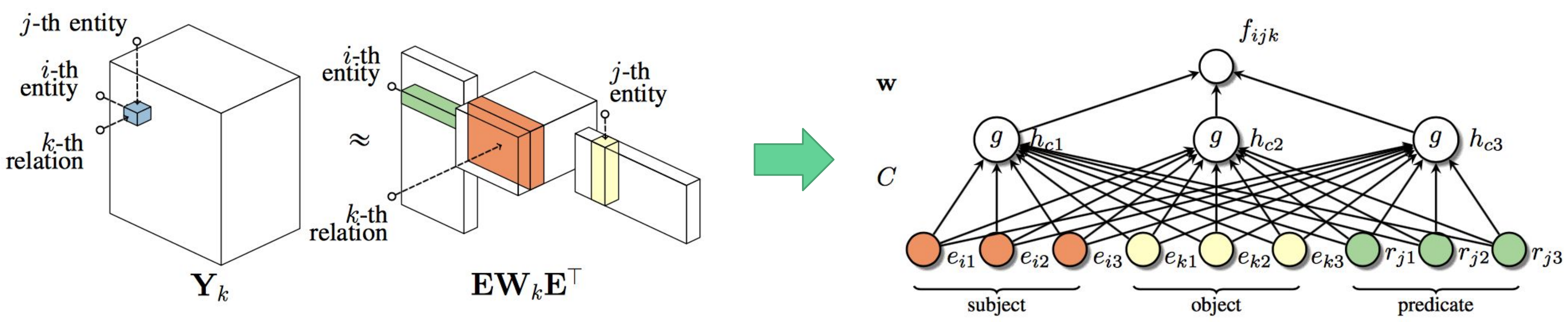
# Knowledge Graph Embeddings [Survey: Nicket et al., 2015]



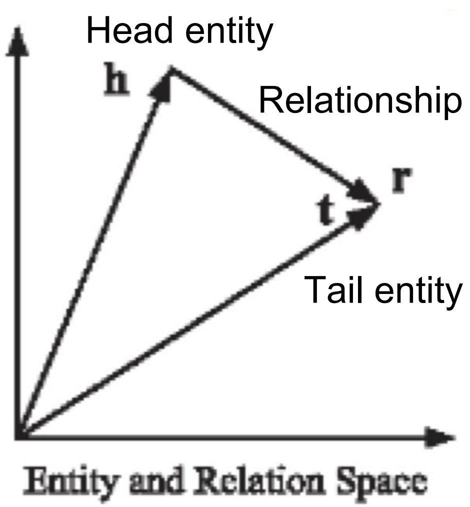

A knowledge graph can be encoded as a tensor.

# Knowledge Graph Embeddings [Survey: Nicket et al., 2015]




Neural networks can be used to obtain richer representations.

# Knowledge Graph Embeddings




- TransE: score(h,r,t)=-$||h+r-t||_{1/2}$
- Hot field with increasing interest [Survey by Wang et al., TKDE 2017]

**Example:** Learn embeddings from IMDb data and identify various types of errors in WikiData [Dong et al., KDD'18]

| Subject | Relation | Target | Reason |
|---|---|---|---|
| The Moises Padilla Story | writtenBy | César Ámigo Aguilar | Linkage error |
| Bajrangi Bhaijaan | writtenBy | Yo Yo Honey Singh | Wrong relationship |
| Piste noire | writtenBy | Jalil Naciri | Wrong relationship |
| Enter the Ninja | musicComposedBy | Michael Lewis | Linkage error |
| The Secret Life of Words | musicComposedBy | Hal Hartley | Cannot confirm |
| ... | ... | ... | ... |

# The Challenge of Training Data

- How much data do we need to train the data fusion model?
- **Theorem:** We need a number of labeled examples proportional to the number of sources [Ng and Jordan, NIPS'01]
- **Model parameters:** Weights related to the error-rates of each data source.

But the number of sources can be in the thousands or millions and training data is limited!

**Idea 1:** Leverage redundancy and used unsupervised learning.
**Idea 2:** Limit model parameters and use a small number of training data.

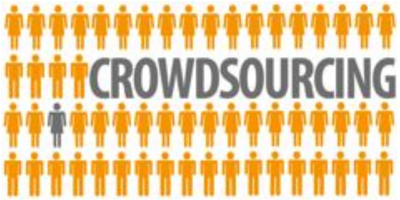
# SLiMFast: Discriminative Data Fusion [Rekatsinas et al., SIGMOD'17]

**Limit the informative parameters of the model by using domain knowledge**

**Key Idea:** Sources have (domain specific) features that are indicative of error rates

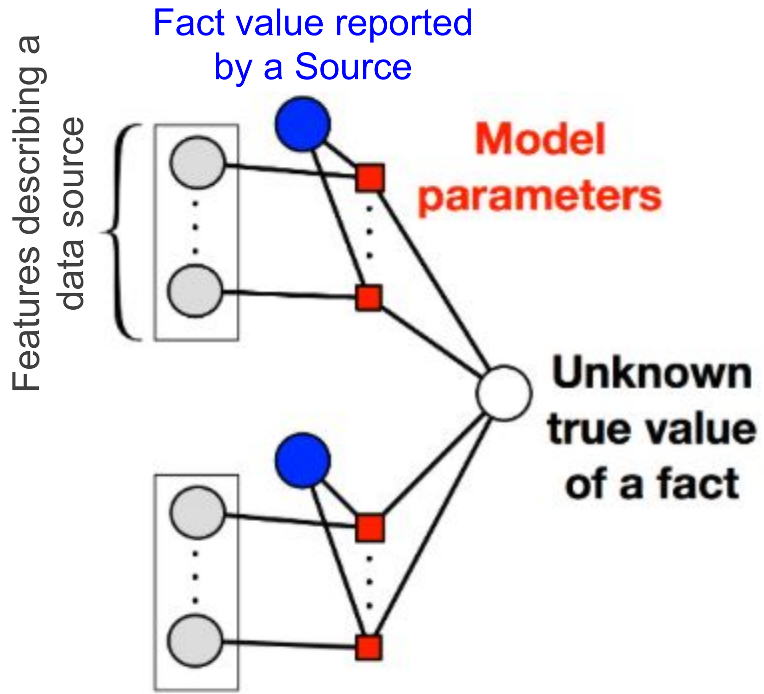
**Example:**

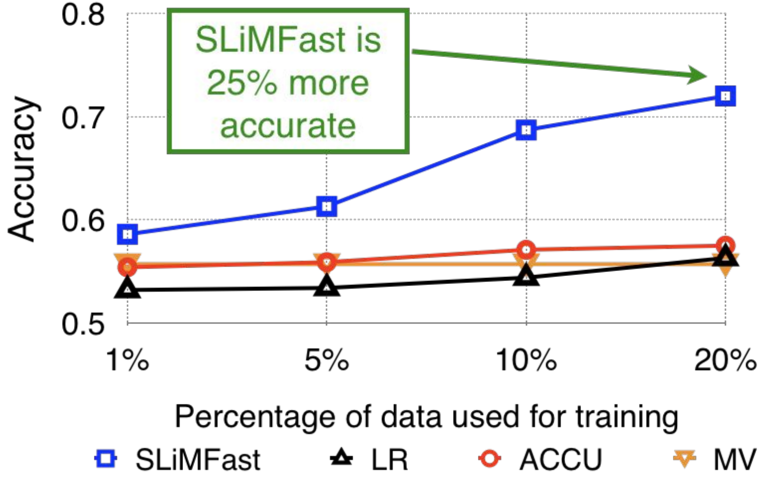

- newly registered similar to existing domain
- traffic statistics
- text quality (e.g., misspelled words, grammatical errors)
- sentiment analysis




- avg. time per task
- number of tasks
- market used

# SLiMFast: Discriminative Data Fusion [Rekatsinas et al., SIGMOD'17]




**Genomics data:** 2.7k sources (articles), 571 objects (gene-disease), 4 domain features (year, citation, author, journal)

# Challenges in Data Fusion

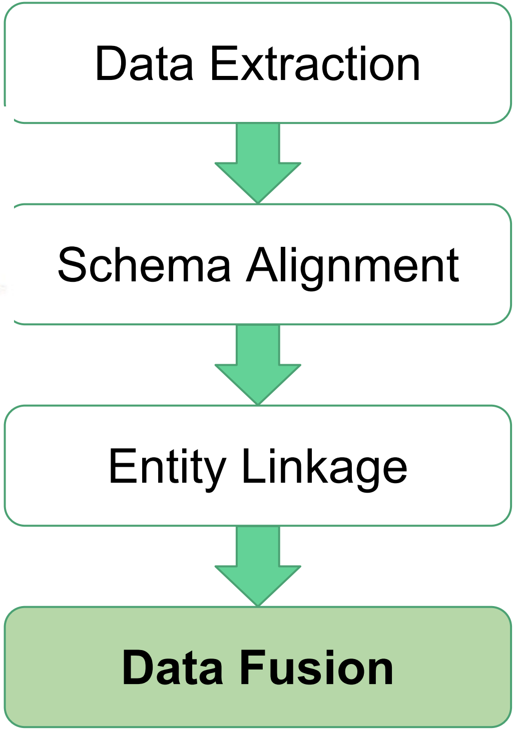
- There are few solutions for unstructured data. Mostly work on fact verification [Tutorial by Dong et al., KDD`2018]. Most data Fusion solutions assume data extraction. Can state-of-the art DL help?

- Using training data is key and semi-supervised learning can significantly improve the quality of Data Fusion results. How can one collect training data effectively without manual annotation?

- We have only scratched the surface of what representation learning and deep learning methods can offer. Can deep learning streamline data fusion? What are its limitations?

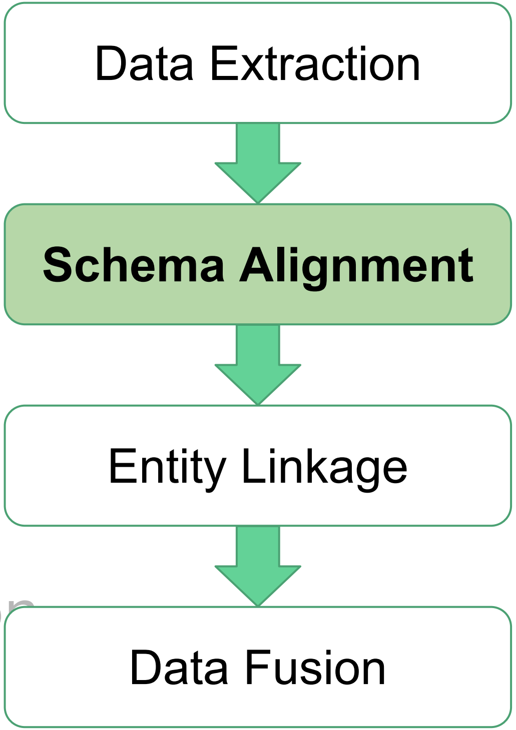
# Recipe for Data Fusion

- Problem definition: **Resolve conflicts and obtain correct values**
- Short answers
  - **Reasoning about source quality is key and works for easy cases**
  - **Semi-supervised learning has shown BIG potential**
  - **Representation learning provides positive evidence for streamlining data fusion.**

# Outline

- Part I. Introduction
- Part II. ML for DI
    - ML for entity linkage
    - ML for data extraction
    - ML for data fusion
    - ML for schema alignment
- Part III. DI for ML
- Part IV. Conclusions and research direction

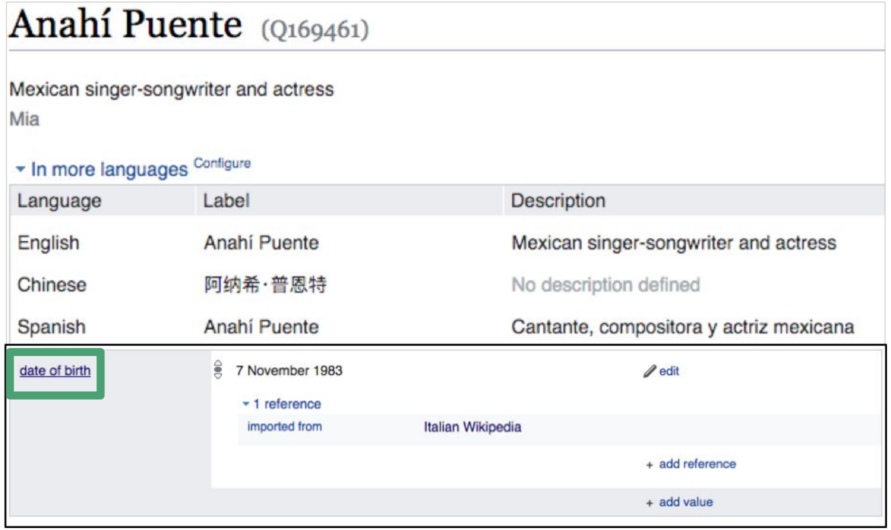


# What is Schema Alignment?

- Definition: Align schemas and understand which attributes have the same semantics.

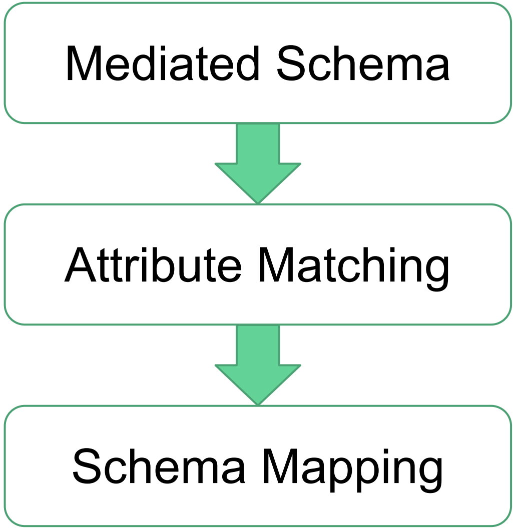
IMDB


WikiData



# Quick Tour for Schema Alignment

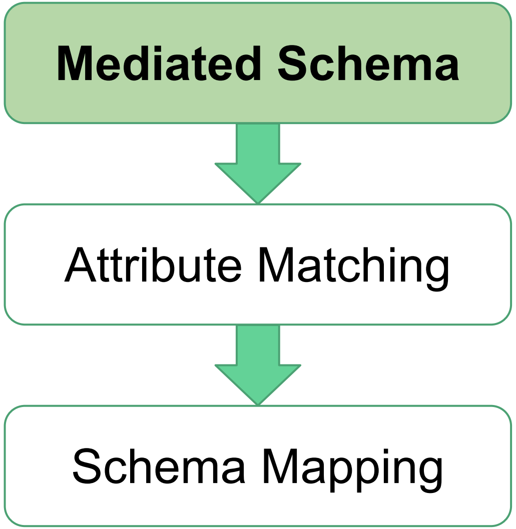
| | |
|---|---|
| S1 | (name, hPhone, hAddr, oPhone, oAddr) |
| S2 | (name, phone, addr, email) |
| S3 | a: (id, name); b: (id, resPh, workPh) |
| S4 | (name, pPh, pAddr) |
| S5 | (name, wPh, wAddr) |



# Quick Tour for Schema Alignment

- **Mediated schema**: a unified and virtual view of the salient aspects of the domain

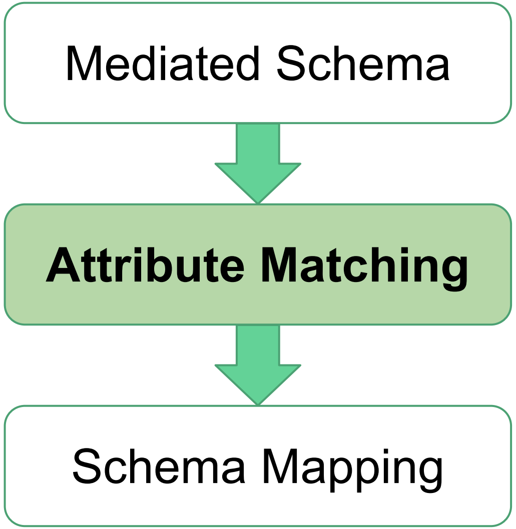
| | |
|---|---|
| S1 | (name, hPhone, hAddr, oPhone, oAddr) |
| S2 | (name, phone, addr, email) |
| S3 | a: (id, name); b: (id, resPh, workPh) |
| S4 | (name, pPh, pAddr) |
| S5 | (name, wPh, wAddr) |
| MS | (n, pP, pA, wP, wA) |



# Quick Tour for Schema Alignment

- **Attribute matching**: correspondences between schema attributes

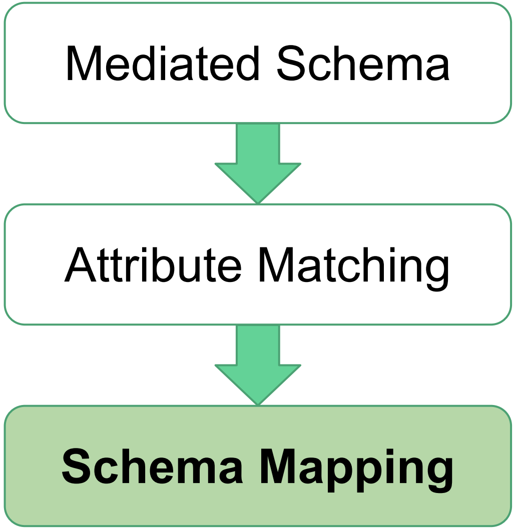
| | |
|---|---|
| S1 | (name, hPhone, hAddr, oPhone, oAddr) |
| S2 | (name, phone, addr, email) |
| S3 | a: (id, name); b: (id, resPh, workPh) |
| S4 | (name, pPh, pAddr) |
| S5 | (name, wPh, wAddr) |
| **MS** | **(n, pP, pA, wP, wA)** |
| **MSAM** | **MS.n**: S1.name, S2.name, S3a.name, …<br>**MS.pP**: S1.hPhone, S3b.resPh, S4.pPh<br>**MS.pA**: S1.hAddr, S4.pAddr<br>**MS.wP**: S1.oPhone, S2.phone, …<br>**MS.wA**: S1.oAddr, S2.addr, S5.wAddr |



# Quick Tour for Schema Alignment

- **Schema mapping**: transformation between records in different schemas

| | |
|---|---|
| S1 | (name, hPhone, hAddr, oPhone, oAddr) |
| S2 | (name, phone, addr, email) |
| S3 | a: (id, name); b: (id, resPh, workPh) |
| S4 | (name, pPh, pAddr) |
| S5 | (name, wPh, wAddr) |
| **MS** | **(n, pP, pA, wP, wA)** |
| **MSSM (GAV)** | MS(n, pP, pA, wP, wA) :- S1(n, pP, pA, wP, wA)<br>MS(n, _, _, wP, wA) :- S2(n, wP, wA, e)<br>MS(n, pP, _, wP, _) :- S3a(i, n), S3b(i, pP, wP)<br>MS(n, pP, pA, _, _) :- S4(n, pP, pA)<br>MS(n, _, _, wP, wA) :- S5(n, wP, wA) |



# 30 Years of Schema Alignment

~1990 (Desc Logics)

**Description Logics**
- Gav vs. Lav. vs. Glav
- Answering queries using views
- Warehouse vs. EII

1994 (Early ML)

**Semi-Auto mapping**
- Learning to match
- Schema mapping: Clio
- Data exchange

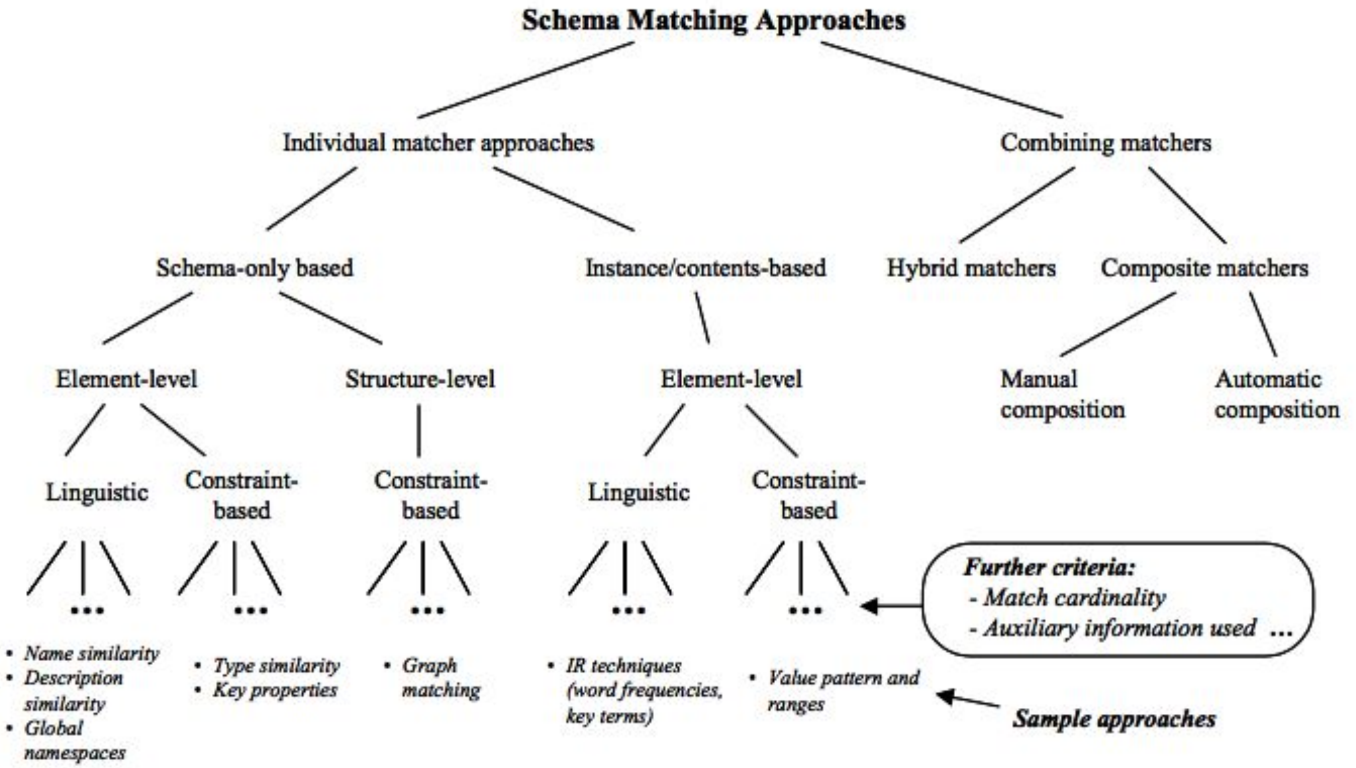
2005 (Dataspaces)

**Pay-as-you-go dataspaces**
- Probabilistic schema alignment

2013 (Deep ML)

**Logic & Deep learning**
- Collective disc. by PSL
- Universal schema

# Early ML Models [Rahm and Bernstein, VLDBJ'2001]




## ~2000 (Early ML)

**Semi-Auto mapping**

- Learning to match
- Schema mapping: Clio
- Data exchange

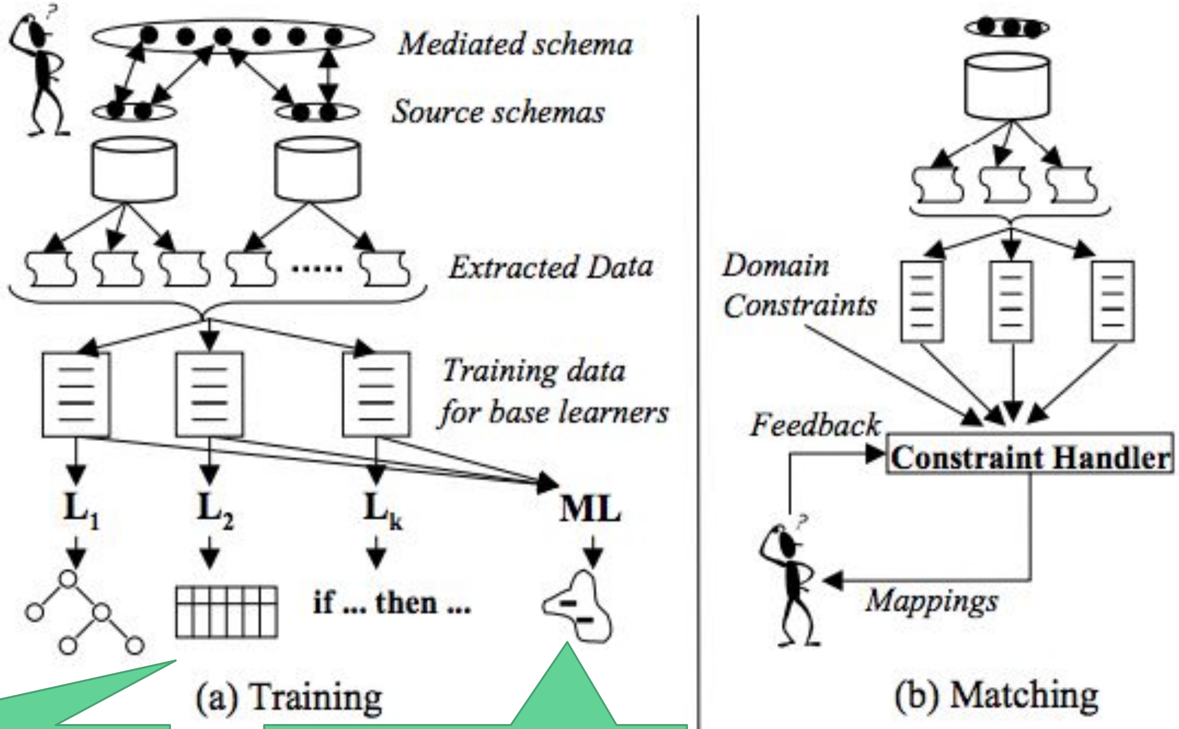
**Signals: name, description, type, key, graph structure, values**

# Early ML Models [Doan et al., Sigmod'01]

## ~2000 (Early ML)

**Semi-Auto mapping**

- Learning to match
- Schema mapping: Clio
- Data exchange




Base learners: kNN, naive Bayes, etc.

Meta learner--Stacking

# Early ML Models

[Doan et al., Sigmod'01]

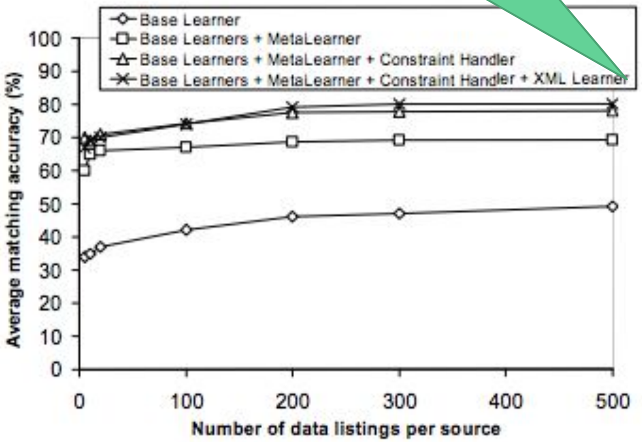
Avg Accuracy: 71-92%

Meta learning and constraints help

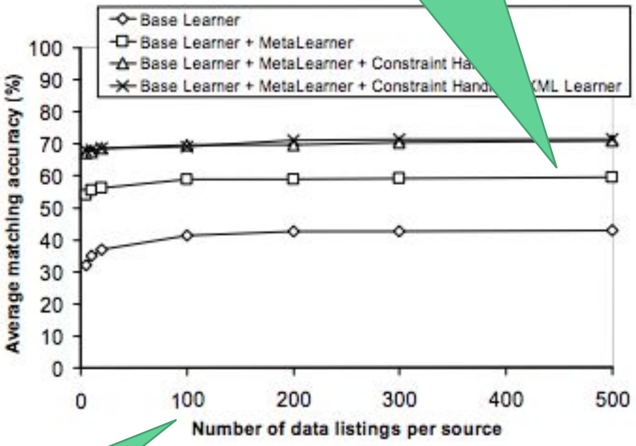
## ~2000 (Early ML)

**Semi-Auto mapping**

- Learning to match
- Schema mapping: Clio
- Data exchange




(b) Matching accuracy for Real Estate I




(c) Matching accuracy for Time Schedule

More data instances help

# Collective Mapping Discovery by PSL [Kimmig et al, ICDE'17]

Step 1. Generate candidate mappings

E.g., $\theta_0$ : $\mathsf{proj}(\mathrm{t}, \mathrm{m}, \mathrm{l}) \wedge \mathsf{emp}(\mathrm{m}, \mathbf{n}, \mathrm{c}) \rightarrow \exists\, \mathrm{o}.\, \mathsf{task}(\mathrm{t}, \mathbf{n}, \mathrm{o})$

$\theta_1$ : $\mathsf{proj}(\mathrm{t}, \mathrm{m}, \mathrm{l}) \wedge \mathsf{emp}(\mathrm{l}, \mathbf{n}, \mathrm{c}) \rightarrow \exists\, \mathrm{o}.\, \mathsf{task}(\mathrm{t}, \mathbf{n}, \mathrm{o})$

$\theta_2$ : $\mathsf{proj}(\mathrm{t}, \mathrm{m}, \mathrm{l}) \wedge \mathsf{emp}(\mathrm{m}, \mathbf{n}, \mathbf{c}) \rightarrow \exists\, \mathrm{o}.\, \mathsf{task}(\mathrm{t}, \mathbf{n}, \mathrm{o}) \wedge \mathsf{org}(\mathrm{o}, \mathbf{c})$

$\theta_3$ : $\mathsf{proj}(\mathrm{t}, \mathrm{m}, \mathrm{l}) \wedge \mathsf{emp}(\mathrm{l}, \mathbf{n}, \mathbf{c}) \rightarrow \exists\, \mathrm{o}.\, \mathsf{task}(\mathrm{t}, \mathbf{n}, \mathrm{o}) \wedge \mathsf{org}(\mathrm{o}, \mathbf{c})$

**2013 (Deep ML)**

Step 2. Solve PSL

1.Prefer fewer mappings: penalty=#atoms

$$\mathsf{size}_{\mathsf{m}}(F): \quad in(F) \rightarrow \perp$$

$$1: \quad J(T) \rightarrow \exists F.\ \mathsf{covers}(F,T) \wedge in(F)$$

$$1: \quad in(F) \wedge \mathsf{creates}(F,T) \rightarrow J(T)$$

**Logic & Deep learning**

- Collective disc. by PSL
- Universal schema

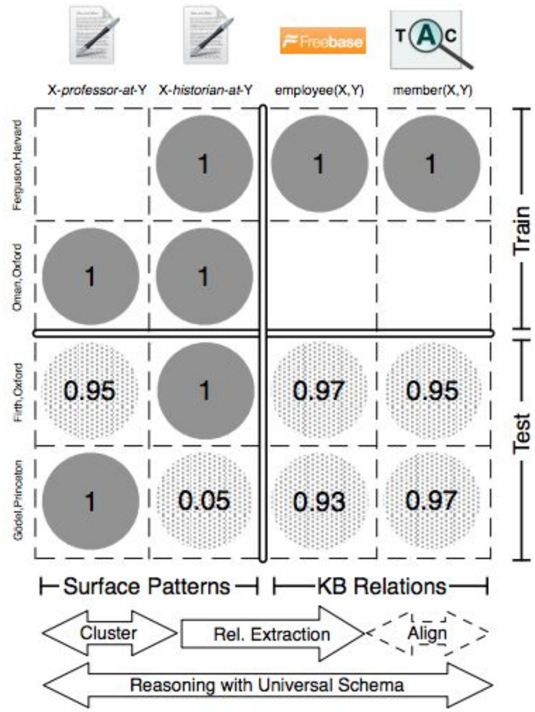
3. Tuples inferred from the mapping should exist

2. An existing tuple can be inferred from the mappings

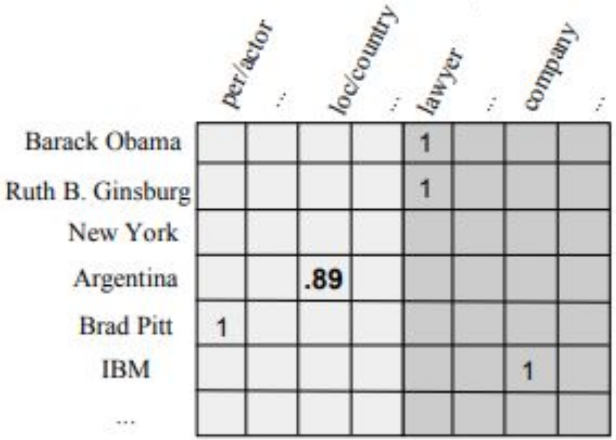
# Universal Schema [Riedel et al., NAACL’13][Yao et al., AKBC’13]

- Attribute matching ➔ Instance inference

## Matrix factorization




**Relation prediction**




**Type prediction**

**2013 (Deep ML)**

**Logic & Deep learning**

- Collective disc. by PSL
- Universal schema

# Universal Schema [Riedel et al., NAACL'13]

## 2013 (Deep ML)

**Logic & Deep learning**
- Collective disc. by PSL
- Universal schema

- Attribute matching ➔ Instance inference
- $f(e_s, r, e_o)$ is computed using embeddings; the higher, the more likely to be true
- DistMult is a relation embedding model

**Limitation: Cannot apply to new entities or relations**

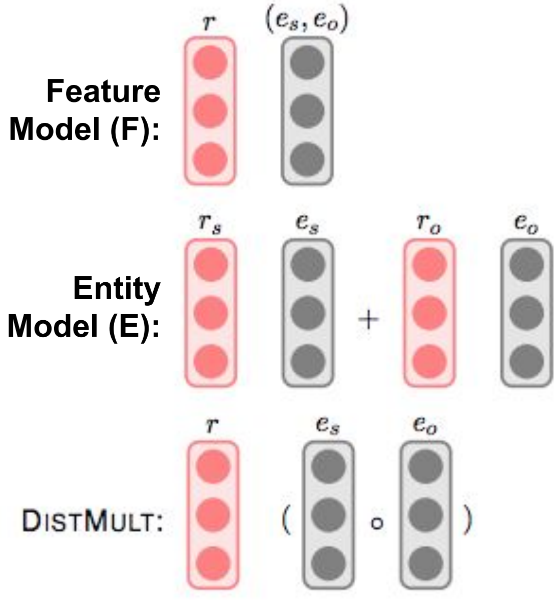



Figure 3: The continuous representations for model F, E and DistMult. [Toutanova et al., EMNLP'15]

# Columnless Univ. Schema w. CNN [Toutanova et al., EMNLP'15]

- Relation: organizationFoundedBy

| Textual Pattern | Count |
|---|---|
| SUBJECT $\xrightarrow{appos}$ founder $\xrightarrow{prep}$ of $\xrightarrow{pobj}$ OBJECT | 12 |
| SUBJECT $\xleftarrow{nsubj}$ co-founded $\xrightarrow{dobj}$ OBJECT | 3 |
| SUBJECT $\xrightarrow{appos}$ co-founder $\xrightarrow{prep}$ of $\xrightarrow{pobj}$ OBJECT | [illegible] |
| SUBJECT $\xrightarrow{conj}$ co-founder $\xrightarrow{prep}$ of $\xrightarrow{pobj}$ OBJECT | [illegible] |
| SUBJECT $\xleftarrow{pobj}$ with $\xleftarrow{prep}$ co-founded $\xrightarrow{dobj}$ OBJECT | [illegible] |
| SUBJECT $\xleftarrow{nsubj}$ signed $\xrightarrow{xcomp}$ establishing $\xrightarrow{dobj}$ OBJECT | 2 |
| SUBJECT $\xleftarrow{pobj}$ with $\xleftarrow{prep}$ founders $\xrightarrow{prep}$ of $\xrightarrow{pobj}$ OBJECT | 2 |
| SUBJECT $\xrightarrow{appos}$ founders $\xrightarrow{prep}$ of $\xrightarrow{pobj}$ OBJECT | 2 |
| SUBJECT $\xleftarrow{nsubj}$ one $\xrightarrow{prep}$ of $\xrightarrow{pobj}$ founders $\xrightarrow{prep}$ of $\xrightarrow{pobj}$ OBJECT | 2 |
| SUBJECT $\xleftarrow{nsubj}$ founded $\xrightarrow{dobj}$ production $\xrightarrow{conj}$ OBJECT | 2 |
| SUBJECT $\xleftarrow{appos}$ partner $\xleftarrow{pobj}$ with $\xleftarrow{prep}$ founded $\xrightarrow{dobj}$ production $\xrightarrow{conj}$ OBJECT | 2 |
| SUBJECT $\xleftarrow{pobj}$ by $\xleftarrow{prep}$ co-founded $\xleftarrow{rcmod}$ OBJECT | 1 |
| SUBJECT $\xleftarrow{nn}$ co-founder $\xrightarrow{prep}$ of $\xrightarrow{pobj}$ OBJECT | 1 |
| SUBJECT $\xrightarrow{dep}$ co-founder $\xrightarrow{prep}$ of $\xrightarrow{pobj}$ OBJECT | 1 |
| SUBJECT $\xleftarrow{nsubj}$ helped $\xrightarrow{xcomp}$ establish $\xrightarrow{dobj}$ OBJECT | 1 |
| SUBJECT $\xleftarrow{nsubj}$ signed $\xrightarrow{xcomp}$ creating $\xrightarrow{dobj}$ OBJECT | 1 |

**Similarity of phrases → CNN**

**2013 (Deep ML)**

**Logic & Deep learning**

- Collective disc. by PSL
- Universal schema

# Columnless Univ. Schema w. CNN [Toutanova et al., EMNLP'15]

**2013 (Deep ML)**

**Logic & Deep learning**

- Collective disc. by PSL
- Universal schema

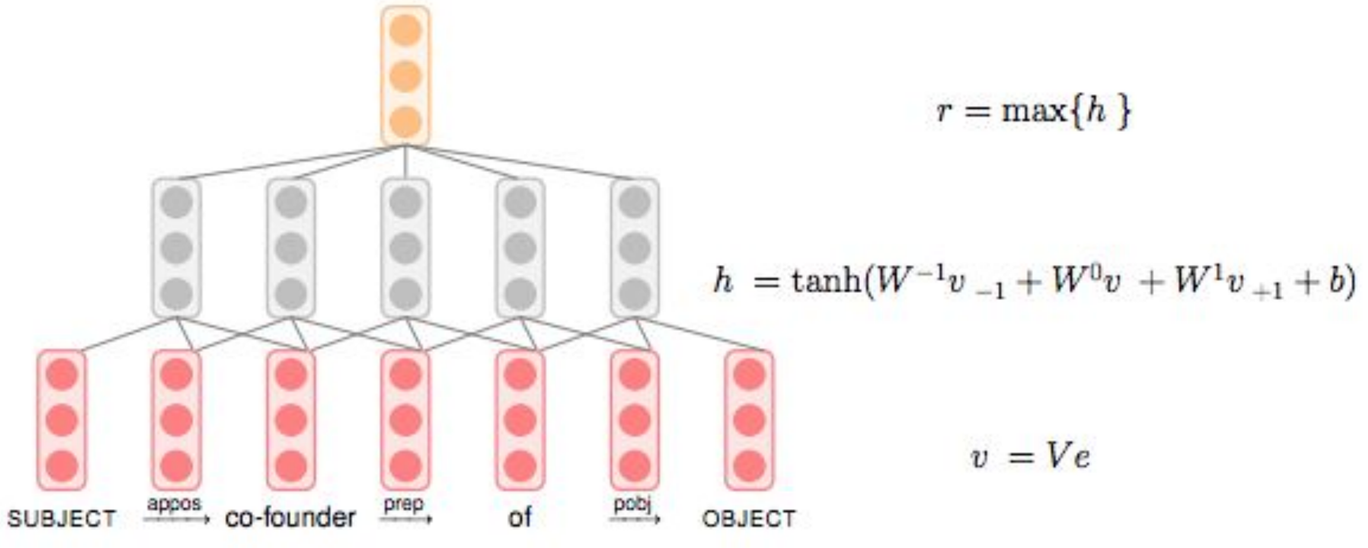
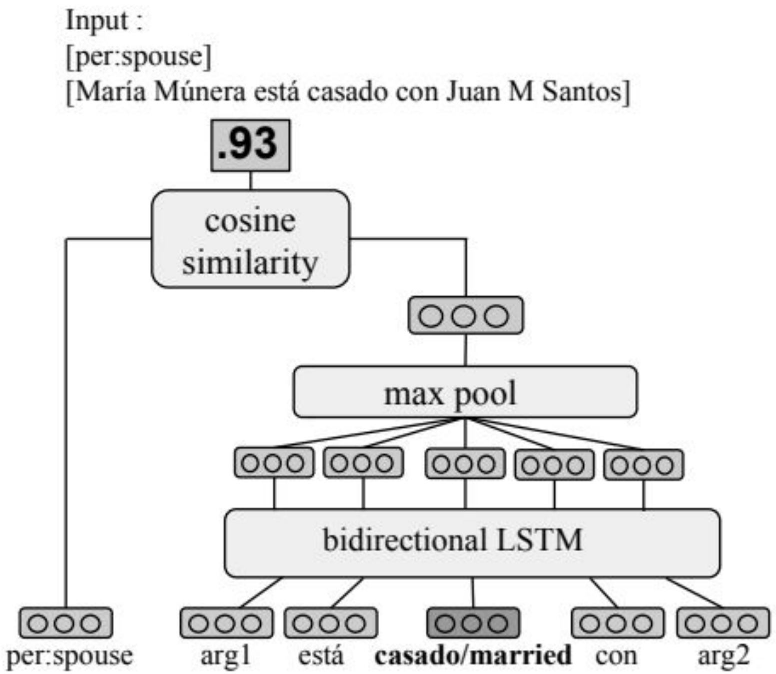



Figure 4: The convolutional neural network architecture for representing textual relations.

# Columnless Univ. Schema w. RNN [Verga et al., ACL'16]

- Similar sequences of context tokens should be embedded similarly




**2013 (Deep ML)**

**Logic & Deep learning**

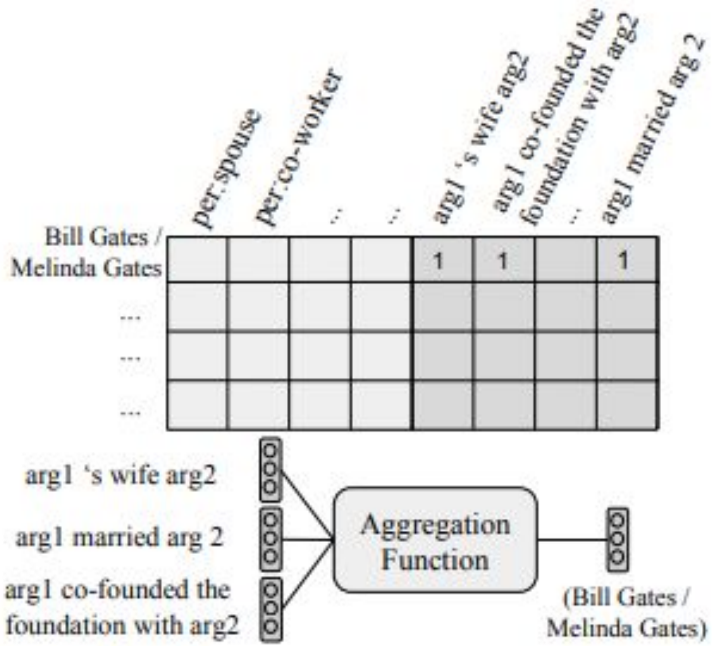
- Collective disc. by PSL
- Universal schema

# Rowless Univ. Schema [Verga et al., ACL’16]

- Infer relation from a set of observed relations
- Similar to schema mapping w. signals from values

**2013 (Deep ML)**

**Logic & Deep learning**
- Collective disc. by PSL
- Universal schema



# Rowless Univ. Schema [Verga et al., ACL'16]

Rowless & Columnless

**2013 (Deep ML)**

**Logic & Deep learning**
- Collective disc. by PSL
- Universal schema

| Model | MRR | Hits@10 |
|---|---|---|
| Entity-pair Embeddings | 31.85 | 51.72 |
| Entity-pair Embeddings-LSTM | **33.37** | 54.39 |
| Attention | 31.92 | 51.67 |
| Attention-LSTM | 30.00 | 53.35 |
| Max Relation | 31.71 | 51.94 |
| Max Relation-LSTM | 30.77 | **54.80** |

(a)

| Model | MRR | Hits@10 |
|---|---|---|
| Entity-pair Embeddings | 5.23 | 11.94 |
| Attention | **29.75** | 49.69 |
| Attention-LSTM | 27.95 | 51.05 |
| Max Relation | 28.46 | 48.15 |
| Max Relation-LSTM | 29.61 | **54.19** |

(b)

Recall still low

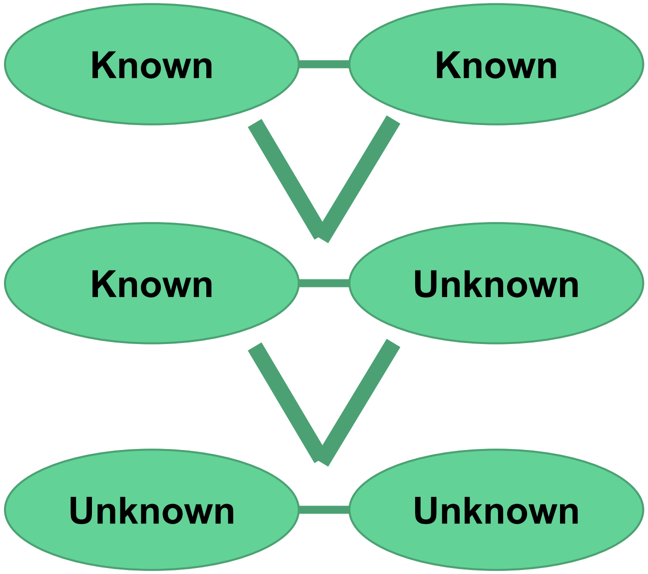
Similar for new entity pairs

# Schema Mapping vs. Universal Schema

| | Schema matching | Universal schema |
|---|---|---|
| *Granularity* | Column-level decision | Cell-level decision |
| *Expressiveness* | Mainly 1:1 mapping | Allow overlap, subset/superset, etc. |
| *Signals* | Name, description, type, key, graph structure, values | Values |
| *Results* | Accu: 70-90% | MRR=~0.3, Hits@10=~0.5 |
| *Community* | Database | NLP |

# Challenges in Applying Deep Learning on SM

- How can we combine techs from schema matching and universal schema??



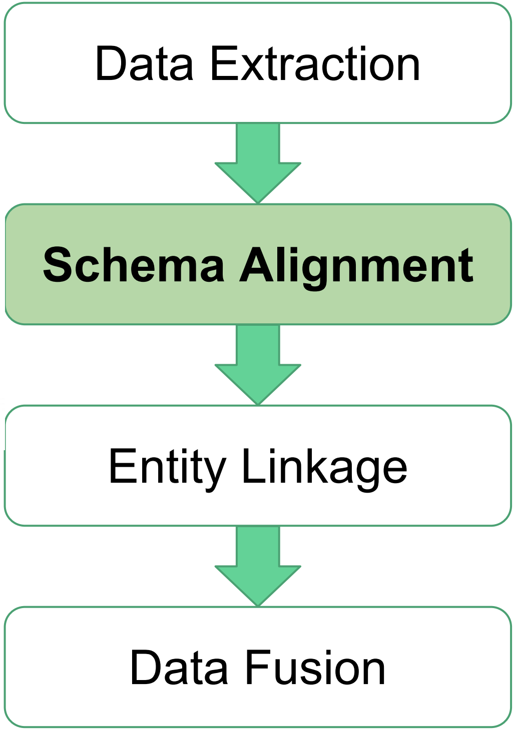

Leverage knowledge by inference

Leverage knowledge on types

Rowless

# Recipe for Schema Alignment

- Problem definition: **Align attributes with the same semantics**
- Short answers
  - **Interactive semi-automatic mapping**
  - **DL-based universal schema revived the field**
  - **Combine schema matching and universal schema for future**

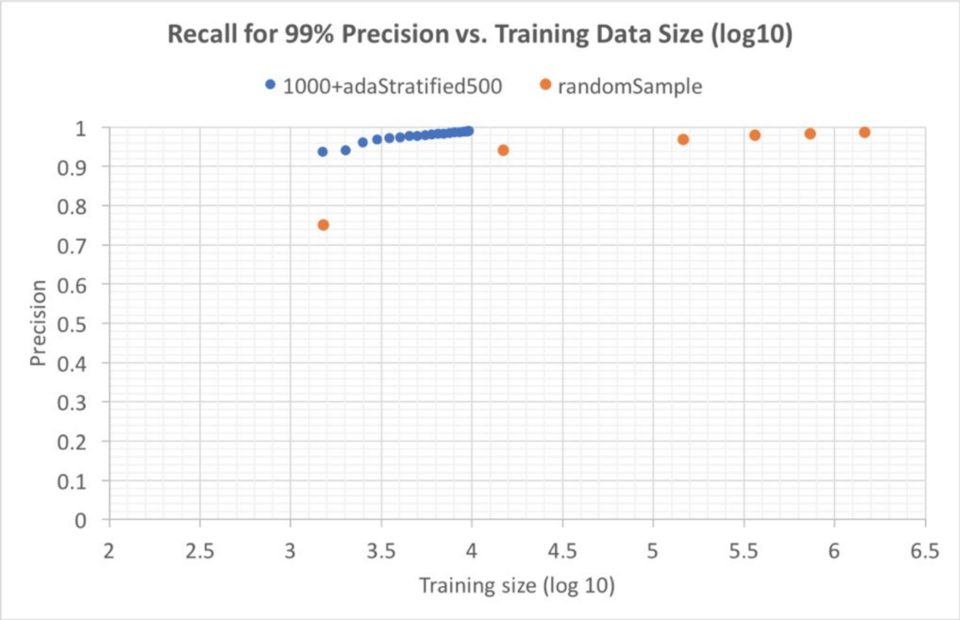



# Revisit Theme I. Which ML Model Works Best?

| DI tasks | Hyperplanes (e.g., Log Reg) | Kernal (e.g., SVM) | Tree-based (e.g., Random forest) | Graphical models (e.g., CRF) | Logic programs (e.g, soft logic) | Neural networks (e.g., RNN) |
|---|---|---|---|---|---|---|
| Entity resolution | X | X | X | | X | X |
| Data fusion | X | | | X | | |
| DOM extraction | X | | | | | |
| Text extraction | X | X | | X | | X |
| Schema alignment | X | | X | X | X | X |

For structured data, RF works well, and LR is often effective
For texts and semantics, deep learning shows big promise

# Revisit Theme II. Does Supervised Learning Apply to DI?




Active learning, semi-supervised learning, and weak supervision lead to dramatically more efficient solutions.

# Outline

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- Part III. DI for ML
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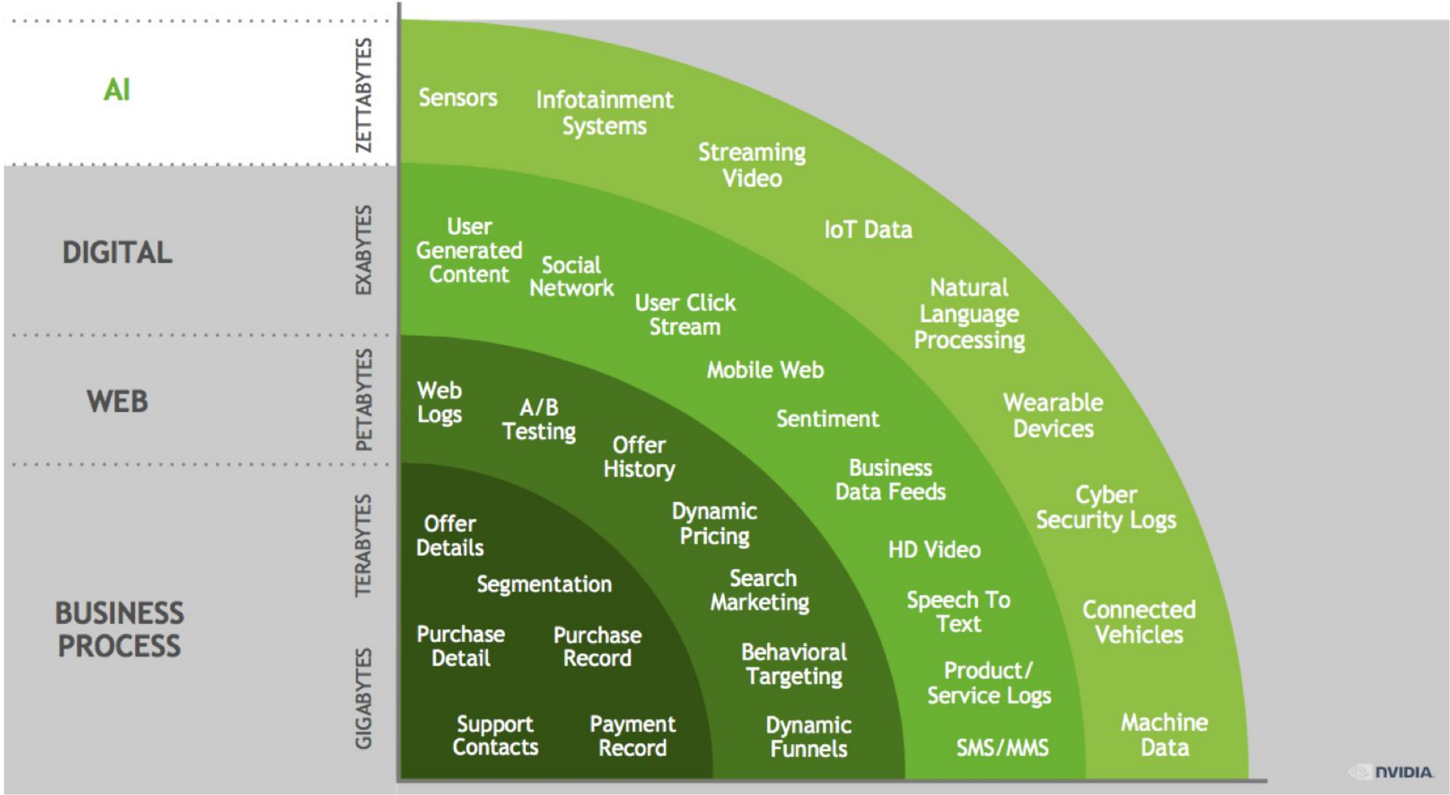
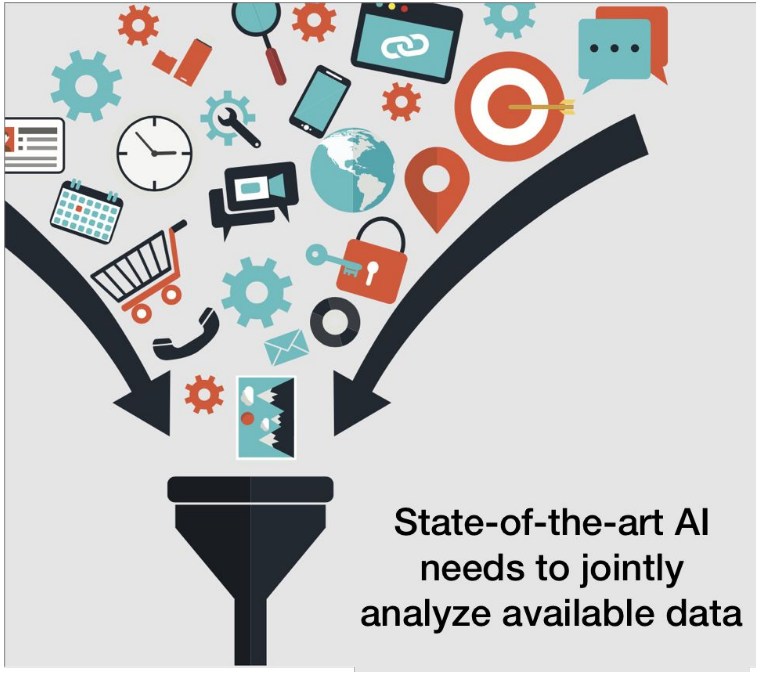
# ML is data-hungry



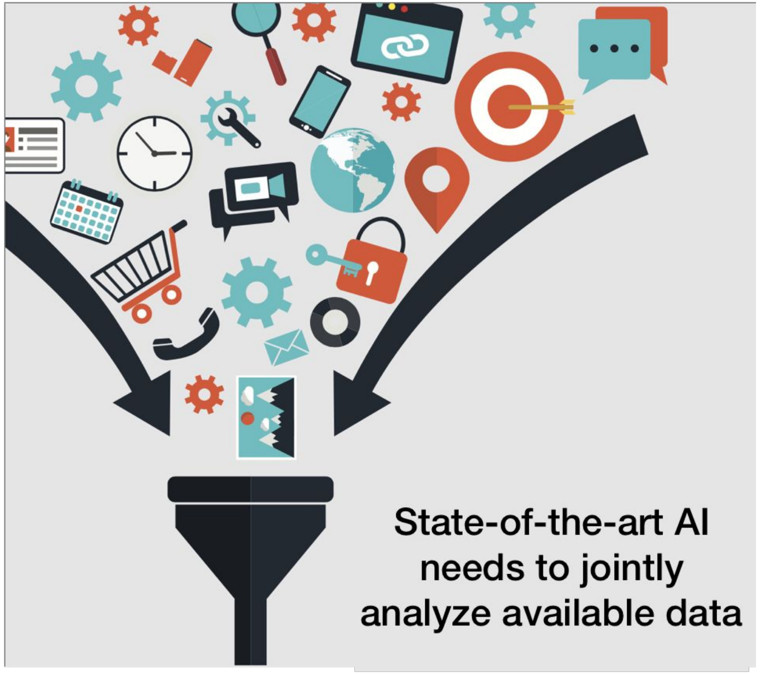
# Successful ML requires Data Integration




IMAGENET MovieLens


Large collections of manually curated training data are necessary for progress in ML.

# Successful ML requires Data Integration




IMAGENET MovieLens


Large collections of manually curated **training data** are necessary for progress in ML.

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# 50 Years of Artificial Intelligence

**1970s (Rules)**

**Expert systems**
- Manually curated knowledge bases of facts and rules
- Use of inference engines
- No support for high-dimensional data

**1990s (Features)**

**Classical ML**
- Low complexity models
- Strong priors that capture domain knowledge (feature engineering)
- Small amounts of training data

**2009 (PGMs)**

**Graphical models and logic**
- Relational statistical learning
- Markov logic network

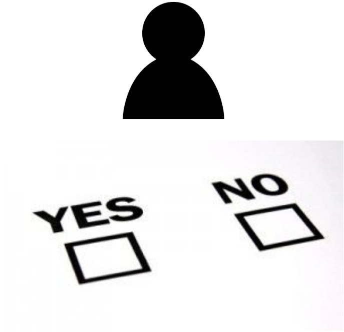
**2010s (Representation Learning)**

**Deep learning**
- Automatically learn representations
- Impressive with high-dimensional data
- Data hungry!

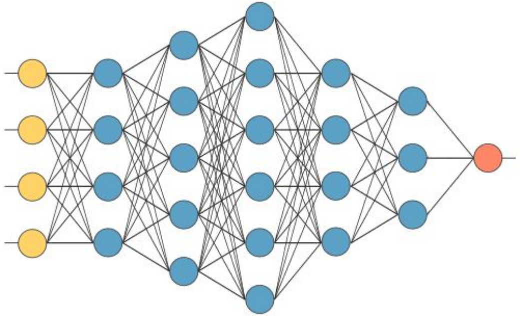
# The ML Pipeline in the Deep Learning Era

**Data Collection**

**Data Labeling**




**Representation Learning and Training**



# The ML Pipeline in the Deep Learning Era

**Data Collection**

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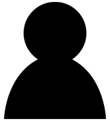
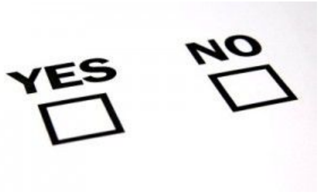
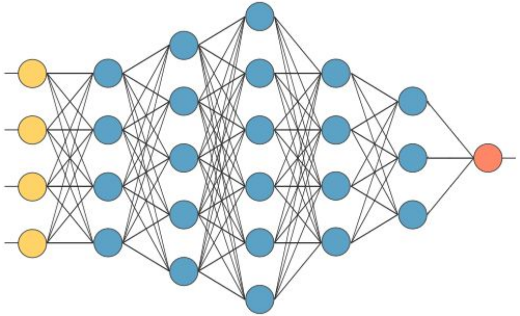





**Representation Learning and Training**



Main pain point today, most time spent in labeling data.

# Training Data: Challenges and Opportunities

- Collecting training data is **expensive** and **slow.**
- We are overfitting to our training data. [Recht et al., 2018]
  - Hand-labeled training data does not change
- Training data is the point to inject domain knowledge
  - Modern ML is too complex to hand-tune features and priors

# Training Data: Challenges and Opportunities

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  - Modern ML is too complex to hand-tune features and priors

***How do we get training data more effectively?***

# The Rise of Weak Supervision

**Definition:** Supervision with noisy (much easier to collect) labels; prediction on a larger set, and then training of a model.

Semi-supervised learning and ensemble learning

**Examples:**

- use of non-expert labelers (crowdsourcing),
- use of curated catalogs (distant supervision)
- use of heuristic rules (labeling functions)

NELL

DeepDive

HoloClean

snorkel

# The Rise of Weak Supervision

- Alexa – Customer embrace of Alexa continues, with Alexa-enabled devices among the best-selling items across all of Amazon. We're seeing extremely strong adoption by other companies and developers that want to create their own experiences with Alexa. There are now more than 30,000 skills for Alexa from outside developers, and customers can control more than 4,000 smart home devices from 1,200 unique brands with Alexa. The foundations of Alexa continue to get smarter every day too. We've developed and implemented an on-device fingerprinting technique, which keeps your device from waking up when it hears an Alexa commercial on TV. (This technology ensured that our Alexa Super Bowl commercial didn't wake up millions of devices.) Far-field speech recognition (already very good) has improved by 15% over the last year; and in the U.S., U.K., and Germany, we've improved Alexa's spoken language understanding by more than 2[illegible]% over the last 12 months through enhancements in Alexa's machine learning components and the use of semi-supervised learning techniques. (These semi-supervised learning techniques reduced the amount of labeled data needed to achieve the same accuracy improvement by 40 times!) Finally, we've dramatically reduced the amount of time required to teach Alexa new languag[illegible] by using machine translation and transfer learning techniques, which allows us to serve customers in more countries (like India and Japan).

# The Rise of Weak Supervision

**Definition:** Supervision with noisy (much easier to collect) labels; prediction on a larger set, and then training of a model.

Related to semi-supervised learning and ensemble learning

**Examples:** use of non-expert labelers (crowdsourcing), use of curated catalogs (distant supervision), use of heuristic rules (labeling functions)

Methods developed to tackle data integration problems are closely related to weak supervision.

# Learning from Crowds [Raykar et al., JMLR'10]

**Setup:** Supervised learning but instead of gold groundtruth one has access to multiple annotators providing (possibly noisy) labels (no absolute gold standard).

**Task:** Learn a classifier from multiple noisy labels.

Closely related to Dawid-Skene!

**Difference:** Estimating the ground truth and the annotator performance is a byproduct here. Goal is to learn a classifier.

# Learning from Crowds [Raykar et al., JMLR'10]

$\mathcal{D} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{N}$

$N$ examples, with labels $\mathbf{y}_i = y_i^1, \ldots, y_I^R$ provided by $R$ different annotators

**Example Task:** Binary classification

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**Example Task:** Binary classification

**Annotator performance:**

*Sensitivity (true positive rate)*

$$\alpha^j = \Pr[y^j = 1 | y = 1]$$

*Specificity ( 1 - false positive rate)*

$$\beta^j = \Pr[y^j = 0 | y = 0]$$

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$$\beta^j = \Pr[y^j = 0 | y = 0]$$

**Learning:** $\Pr[\mathcal{D}|\theta] = \prod_{i=1}^N [a_i p_i + b_i(1 - p_i)]$

$$\boxed{p_i := \sigma(\boldsymbol{w}^\top \boldsymbol{x}_i).}$$

$$a_i := \prod_{j=1}^R [\alpha^j]^{y_i^j} [1 - \alpha^j]^{1-y_i^j}.$$

$$b_i := \prod_{j=1}^R [\beta^j]^{1-y_i^j} [1 - \beta^j]^{y_i^j}.$$

Model parameters {**w**, ***α***, ***β***}

EM algorithm to obtain maximum-likelihood estimates.

Difference with Dawid-Skene is the estimation of *w*.

# Distant Supervision [Mintz et al., ACL'09]

**Goal:** Extracting structured knowledge from text.

**Hypothesis:** If two entities belong to a certain relation, any sentence containing those two entities is likely to express that relation.

**Idea:** Use a *database* of relations to gets lots of *noisy* training examples

- Instead of hand-creating seed tuples (bootstrapping)
- Instead of using hand-labeled corpus (supervised)

**Benefits:** has the advantages of supervised learning (leverage reliable hand-created knowledge), has the advantages of unsupervised learning (leverage unlimited amounts of text data).

# Distant Supervision [Mintz et al., ACL'09]

**Corpus Text**

Bill Gates founded Microsoft in 1975.
Bill Gates, founder of Microsoft, …
Bill Gates attended Harvard from …
Google was founded by Larry Page …

**Training Data**

**Freebase**

(Bill Gates, Founder, Microsoft)
(Larry Page, Founder, Google)
(Bill Gates, CollegeAttended, Harvard)

[Adapted example from Luke Zettlemoyer]

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(Bill Gates, Microsoft)
Label: Founder
Feature: X founded Y

[Adapted example from Luke Zettlemoyer]

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Label: Founder
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Feature: X, founder of Y

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(Bill Gates, Founder, Microsoft)
(Larry Page, Founder, Google)
(Bill Gates, CollegeAttended, Harvard)

**Training Data**

(Bill Gates, Microsoft)
Label: Founder
Feature: X founded Y
Feature: X, founder of Y

(Bill Gates, Harvard)
Label: CollegeAttended
Feature: X attended Y

For negative examples, sample unrelated pairs of entities.

[Adapted example from Luke Zettlemoyer]

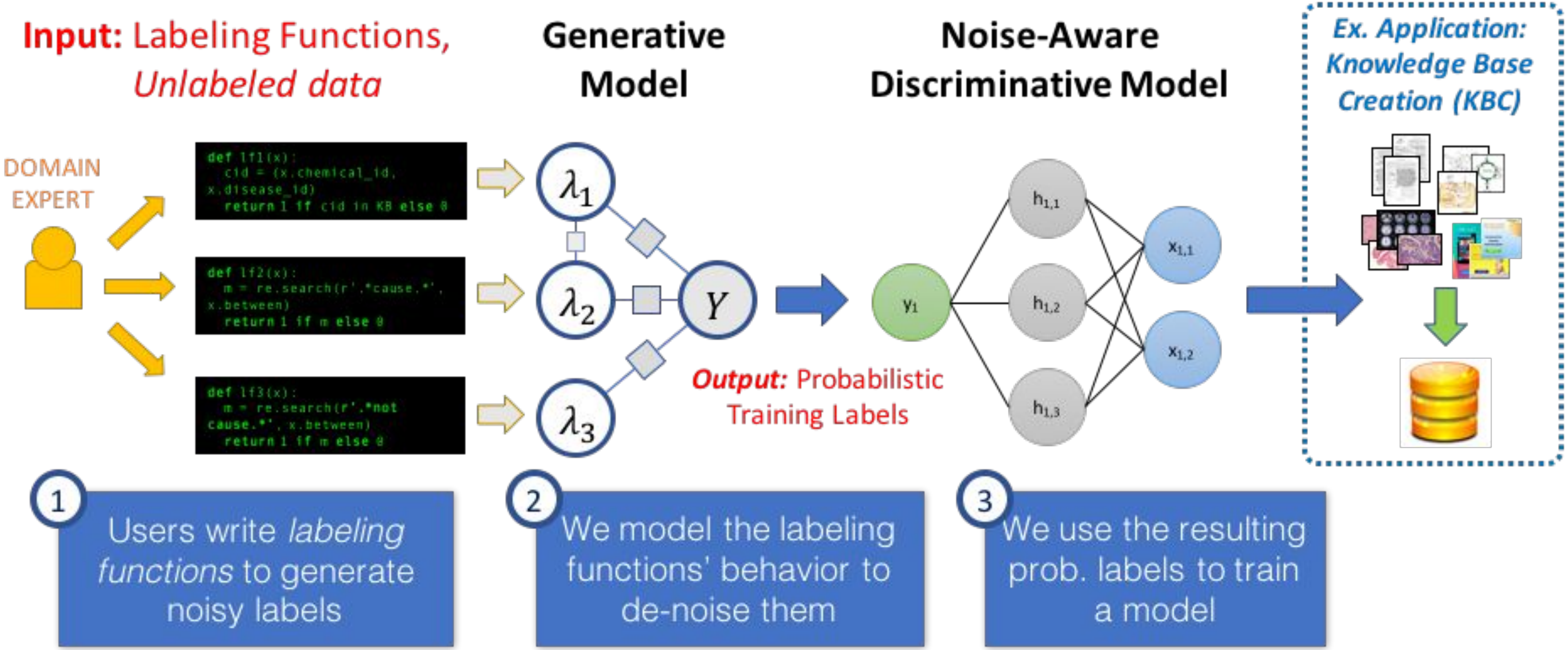
# Distant Supervision [Mintz et al., ACL'09]

**Entity Linking** is an inherent problem in Distant Supervision.

The quality of matches can vary significantly and has a direct effect on extraction quality.

| Relation | Freebase Matches | |
|---|---|---|
| | #sents | % true |
| /business/person/company | 302 | 89.0 |
| /people/person/place_lived | 450 | 60.0 |
| /location/location/contains | 2793 | 51.0 |
| /business/company/founders | 95 | 48.4 |
| /people/person/nationality | 723 | 41.0 |
| /location/neighborhood/neighborhood_of | 68 | 39.7 |
| /people/person/children | 30 | 80.0 |
| /people/deceased_person/place_of_death | 68 | 22.1 |
| /people/person/place_of_birth | 162 | 12.0 |
| /location/country/administrative_divisions | 424 | 0.2 |

# Snorkel: Code as Supervision [Ratner et al., NIPS'16, VLDB'18]




[Slide by Alex Ratner]

# Snorkel: Code as Supervision [Ratner et al., NIPS'16, VLDB'18]

NIH NLM

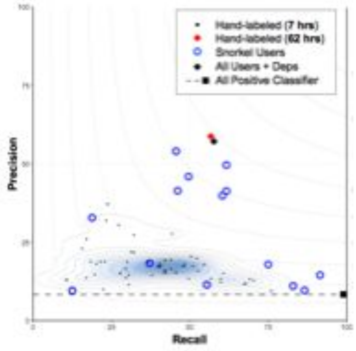
mobilize
Center for Mobility Data
Integration to Insight

Snorkel biomedical workshop in collaboration with the NIH Mobilize Center

15 companies and research groups attended

Cleveland Clinic · WISCONSIN · Caltech · Stanford Hospital & Clinics · W2O GROUP · BCM Baylor College of Medicine · AI2 ALLEN INSTITUTE for ARTIFICIAL INTELLIGENCE

How well did these new Snorkel users do?




**71%** New Snorkel users matched or beat 7 hours of hand-labeling

**2.8x** Faster than hand-labeling data

**45.5%** Average improvement in model performance


## 3rd Place Score

No machine learning experience

Beginner-level Python

[Slide by Alex Ratner]

# Alex (the creator of Snorkel) is on the market!

Alex Ratner

https://ajratner.github.io

You can find Alex at the poster session tonight!

# Challenges in Creating Training Data

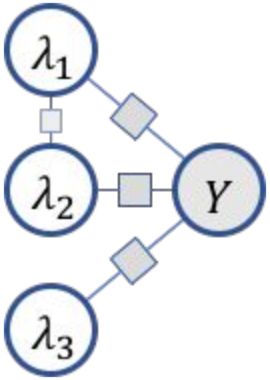
- Richly-formatted data is still a challenge. How can attack weak supervision when data includes images, text, tables, video, etc.?

- Combining weak supervision with other data enrichment techniques such as data augmentation is an exciting direction. How can reinforcement learning help here (http://goo.gl/K2qopQ)?
- How can we combine weak supervision with techniques from semi-supervised?

- Most work on weak supervision focuses on text or images. What about relational data? How can weak supervision be applied there?

# Recipe for Creating Training Data

- Problem definition: **Go beyond gold labels to noisy training data.**
- Short answers
  - **Transition from "gold" labels to "high-confidence" labels.**
  - **Modeling error rates is key. The notion of *data source* is different.**
  - **Need for debugging tools, bias detection, and recommendations of weak supervision signals.**



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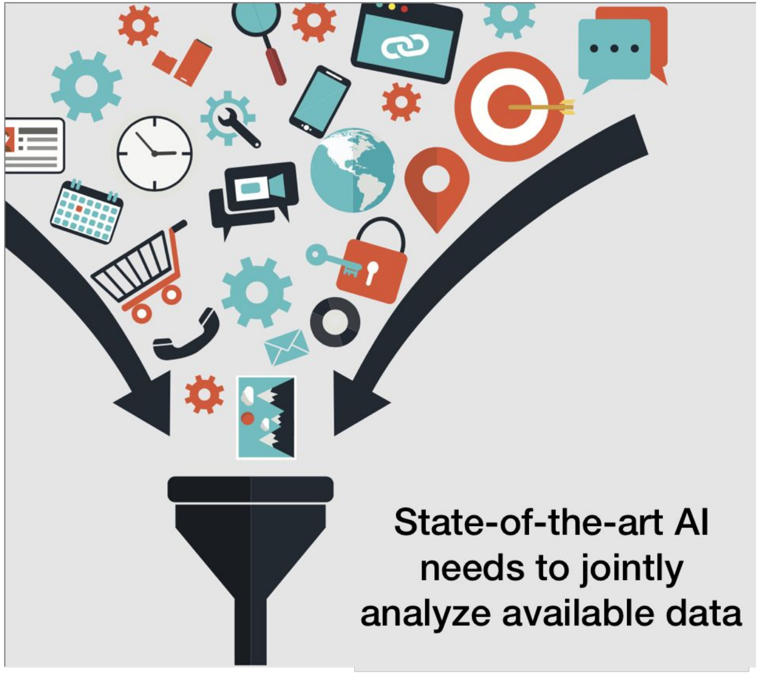
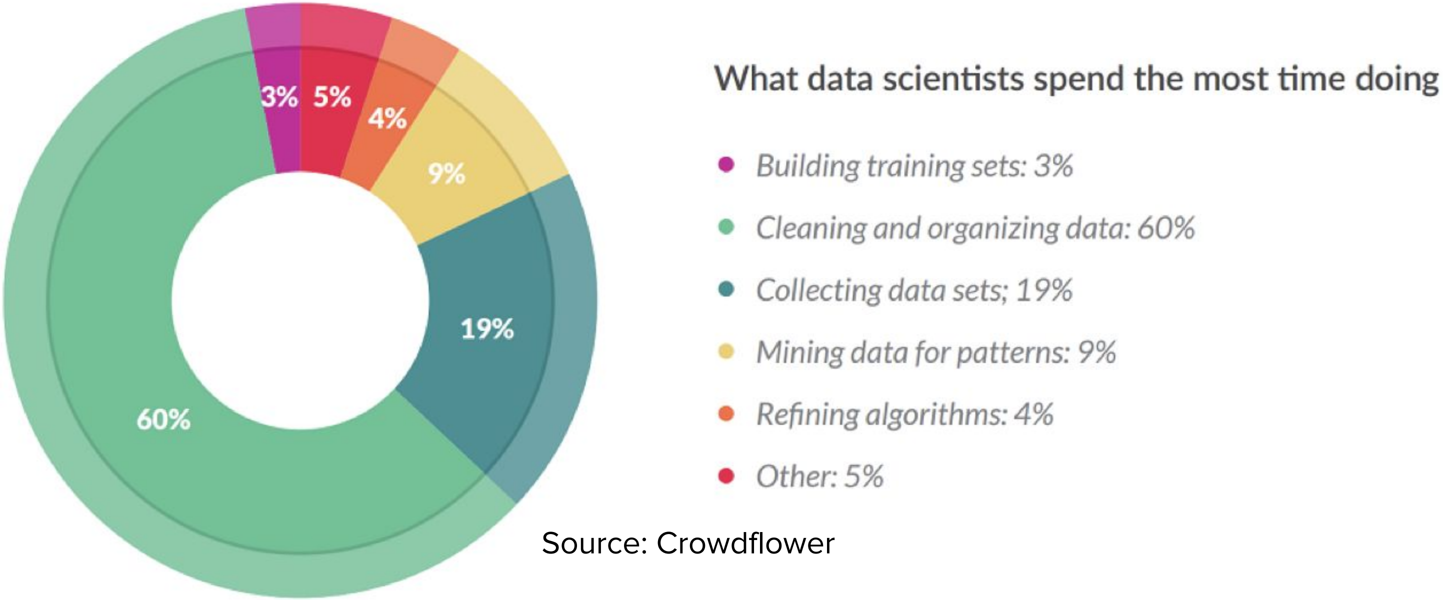
# Successful ML requires Data Integration




IMAGENET MovieLens


Large collections of **manually curated** training data are necessary for progress in ML.

# Noisy data is a bottleneck




Source: Crowdflower

Cleaning and organizing data comprises 60% of the time spent on an analytics of AI project.

# 50 Years of Data Cleaning

**1970s (Nulls)**

**E. F. Codd**

- Understanding relations (installment #7). *FDT - Bulletin of ACM SIGMOD*, 7(3):23–28, 1975.
- Null-related features of DBs

**1980s (Normalization)**

**Integrity Constraints**

- Normal forms to reduce redundancy and integrity
- FDs, MVDs etc.

**1990s (Warehouses)**

**Data transforms**

- Part of ETL
- Errors within a source and across sources
- Transformation workflows and mapping rules; domain-knowledge is crucial

**2000s (Data Repairs)**

**Constraints and Probabilities**

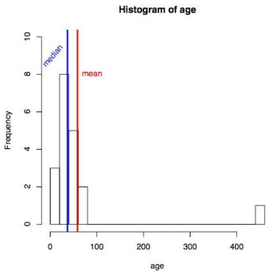
- Dichotomies for consistent query answering
- Minimality-based repairs to obtain consistent instances
- Statistical repairs
- Anomaly detection

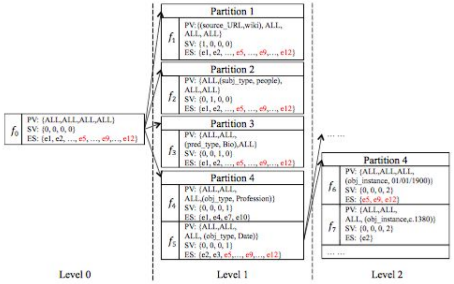
# Where are we today?

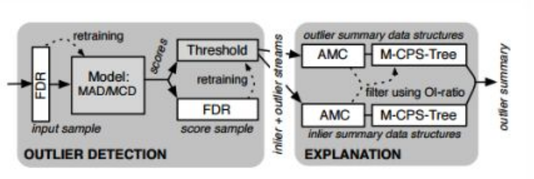
Machine learning and statistical analysis are becoming more prevalent.

***Error detection (Diagnosis)***

- Anomaly detection [Chandola et al., ACM CSUR, 2009]
- Bayesian analysis (Data X-Ray) [Wang et al., SIGMOD'15]
- Outlier detection over streams (Macrobase) [Bailis et al., SIMGOD'17]



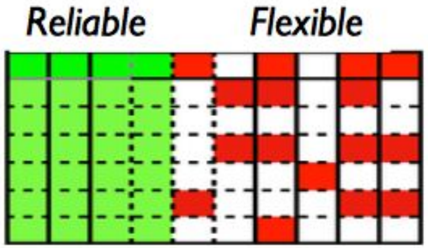



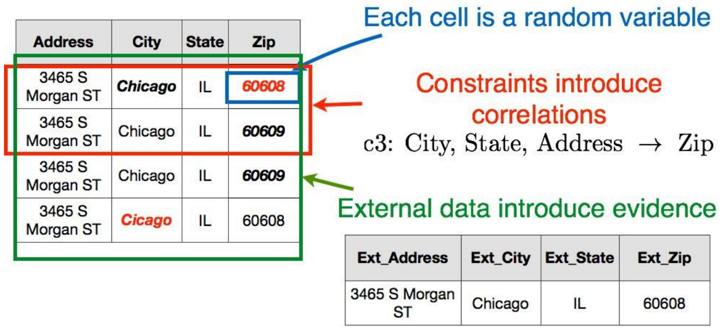
# Where are we today?

Machine learning and statistical analysis are becoming more prevalent.

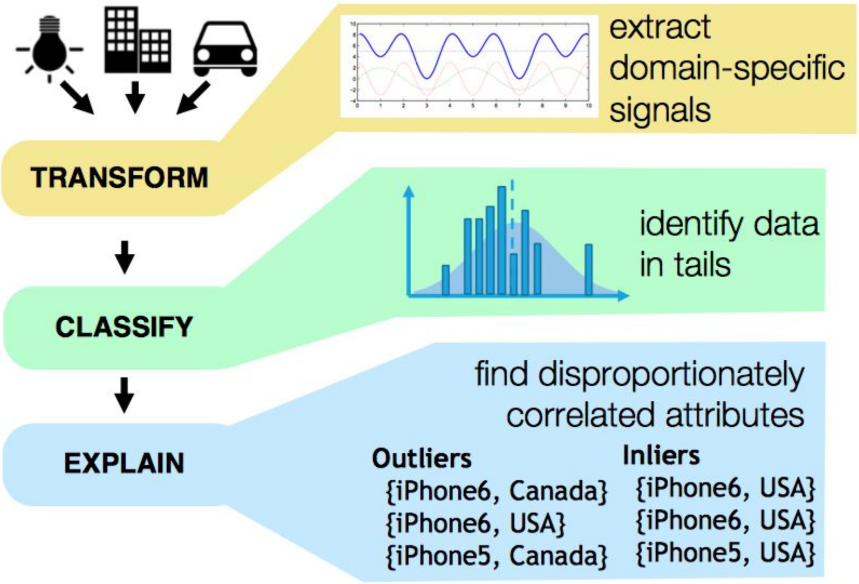
***Data Repairing (Treatment)***

- Classical ML (SCARE, ERACER) [Yakout et al., VLDB'11, SIGMOD'13, Mayfield et al., SIGMOD'10]
- Boosting [Krishan et al., 2017]
- Weakly-supervised ML (HoloClean) [Rekatsinas et al., VLDB'17]




# Error Detection: MacroBase [Bailis et al., SIGMOD'17]




[Figure by Kai Sheng Tai]

**Streaming Feature Selection**

**Setup:** Online learning of a classifier (e.g., LR)

**Goal:** Return top-k discriminative features

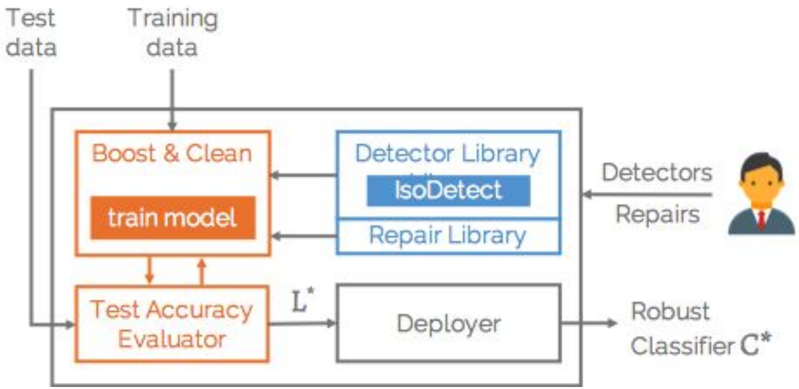
**Weight-Median Sketch**

Sketch of a classifier for fast updates and queries for estimates of each weight and comes with approximation guarantees

A data analytics tool that prioritizes attention in large datasets.

**Code at: macrobase.stanford.edu**

# Data Repairing: BoostClean [Krishnan et al., 2017]




**Ensemble learning for error detection and data repairing.**

Relies on domain-specific detection and repairing.

Builds upon boosting to identify repairs that will maximize the performance improvement of a downstream classifier.

On-demand cleaning!

# Scalable machine learning for data enrichment

HoloClean

Code available at:

**http://www.holoclean.io**

# Data Repairing: HoloClean [Rekatsinas et al., VLDB’17]

| | Address | City | State | Zip |
|---|---|---|---|---|
| t1 | 3465 S Morgan ST | *Chicago* | IL | *60608* |
| t2 | 3465 S Morgan ST | Chicago | IL | *60609* |
| t3 | 3465 S Morgan ST | Chicago | IL | *60609* |
| t4 | 3465 S Morgan ST | *Cicago* | IL | *60608* |

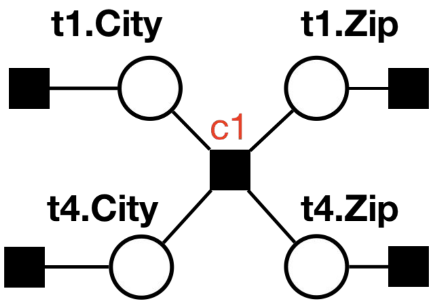
Each cell is a random variable

Value co-occurrences capture data statistics

Constraints introduce correlations

$$\text{c1: Zip} \rightarrow \text{City}$$

“Address= 3465 S Morgan St”




: Unknown (to be inferred) RV

: Factor (encodes correlations)

**Holistic data cleaning framework:** combines a variety of heterogeneous signals (e.g., integrity constraints, external knowledge, quantitative statistics)

# Data Repairing: HoloClean [Rekatsinas et al., VLDB'17]

| | Address | City | State | Zip |
|---|---|---|---|---|
| t1 | 3465 S Morgan ST | *Chicago* | IL | *60608* |
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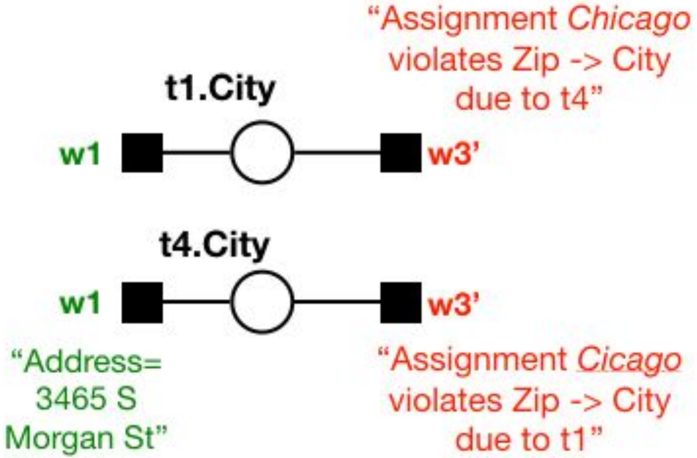
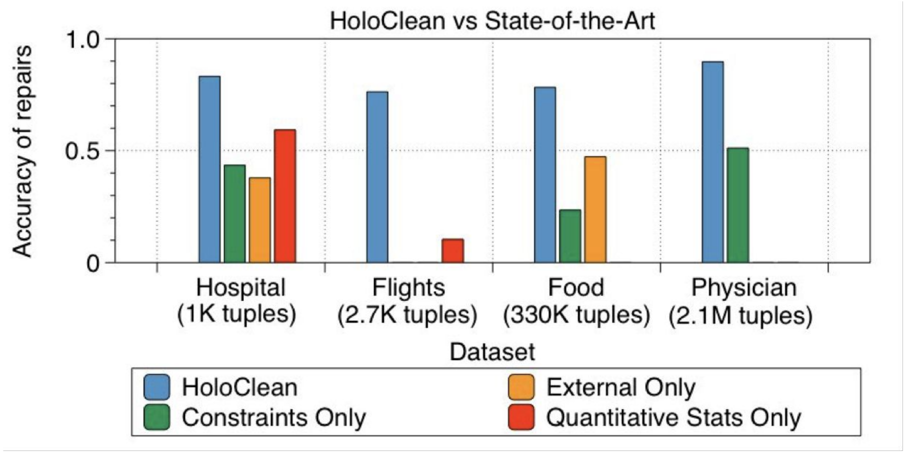
| t4 | 3465 S Morgan ST | *Cicago* | IL | *60608* |




**Scalable learning and inference:** Hard constraints lead to complex and non-scalable models. Novel relaxation to features over individual cells.

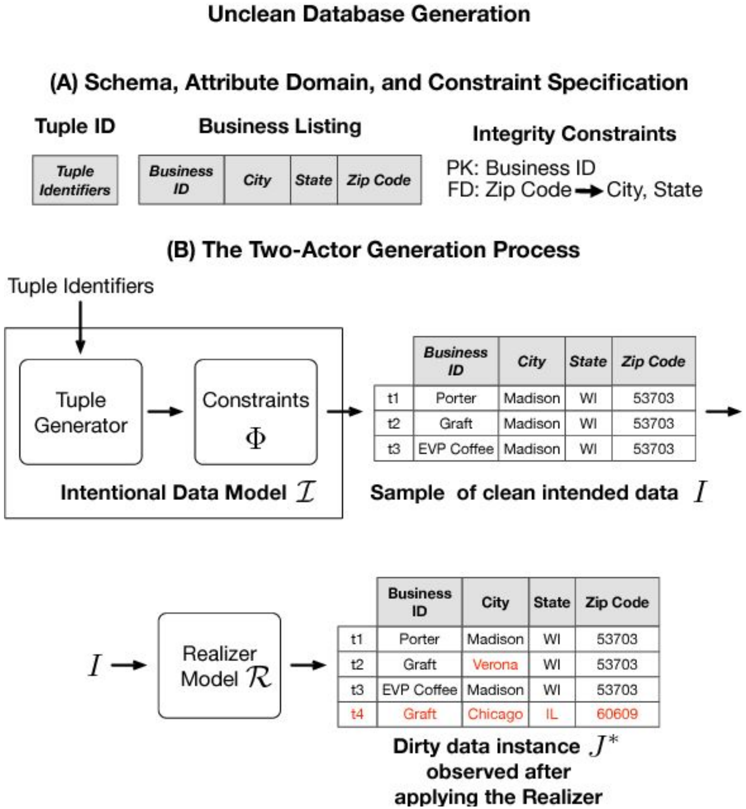
# Data Repairing: HoloClean [Rekatsinas et al., VLDB'17]




**HoloClean:** our approach combining all signals and using inference
**Holistic[Chu,2013]:** state-of-the-art for constraints & minimality
**KATARA[Chu,2015]:** state-of-the-art for external data
**SCARE[Yakout,2013]:** state-of-the-art ML & qualitative statistics

HoloClean is 2x more accurate. Competing methods either do not scale or perform no correct repairs.

# Probabilistic Unclean Databases [De Sa et al., 2018]




A two-actor noisy channel model for managing erroneous data.

Preprint: *A Formal Framework For Probabilistic Unclean Databases*

https://arxiv.org/abs/1801.06750

# Challenges in Data Cleaning

- Error detection is still a challenge. To what extent is ML useful for error detection? Tuple-scoped approaches seem to be dominating. Is deep learning useful?

- We need a formal framework to describe when automated solutions are possible.

- A major bottleneck is the collection of training data. Can we leverage weak supervision and data augmentation more effectively?

- Limited end-to-end solutions. Data cleaning workloads (mixed relational and statistical workloads) pose unique scalability challenges.

# Recipe for Data Cleaning

- Problem definition: **Detect and repair erroneous data.**
- Short answers
  - **ML can help partly-automate cleaning. Domain-expertise is still required.**
  - **Scalability of ML-based data cleaning methods is a pressing challenge. Exciting systems research!**
  - **We need more end-to-end systems!**

| Address | City | State | Zip |
|---|---|---|---|
| 3465 S Morgan ST | ***Chicago*** | IL | ***60608*** |
| 3465 S Morgan ST | Chicago | IL | ***60609*** |
| 3465 S Morgan ST | Chicago | IL | ***60609*** |
| 3465 S Morgan ST | ***Cicago*** | IL | 60608 |

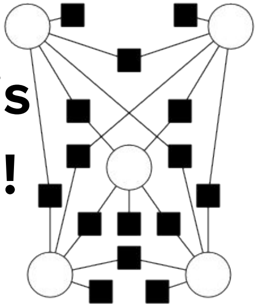
Each cell is a random variable

Constraints introduce correlations

c3: City, State, Address $\rightarrow$ Zip

External data introduce evidence

| Ext_Address | Ext_City | Ext_State | Ext_Zip |
|---|---|---|---|
| 3465 S Morgan ST | Chicago | IL | 60608 |



# Outline

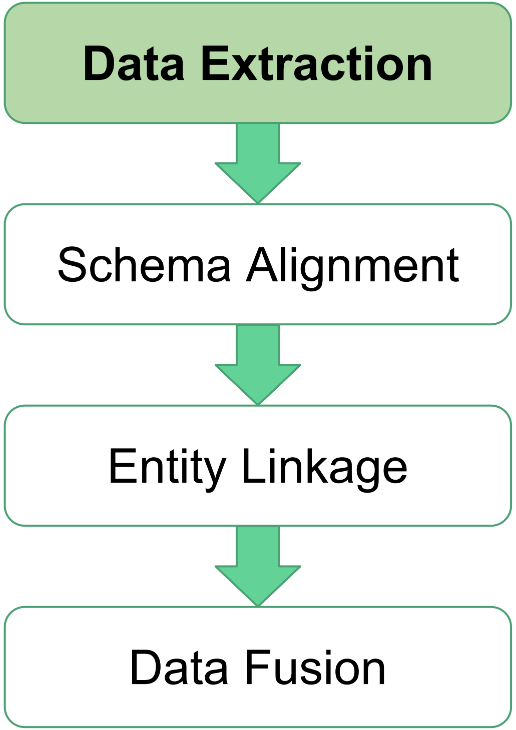
- Part I. Introduction
- Part II. ML for DI
- Part III. DI for ML
  - Creating training data
  - Data cleaning
- Part IV. Conclusions and research direction

# DI and ML: A Natural Synergy

- Data integration is one of the oldest problems in data management
- Transition from logic to probabilities revolutionized data integration
  - Probabilities allow us to reason about inherently noisy data
  - Similar to the AI-revolution in the 80s [https://vimeo.com/48195434]
- Modern machine learning and deep learning have the power to streamline DI

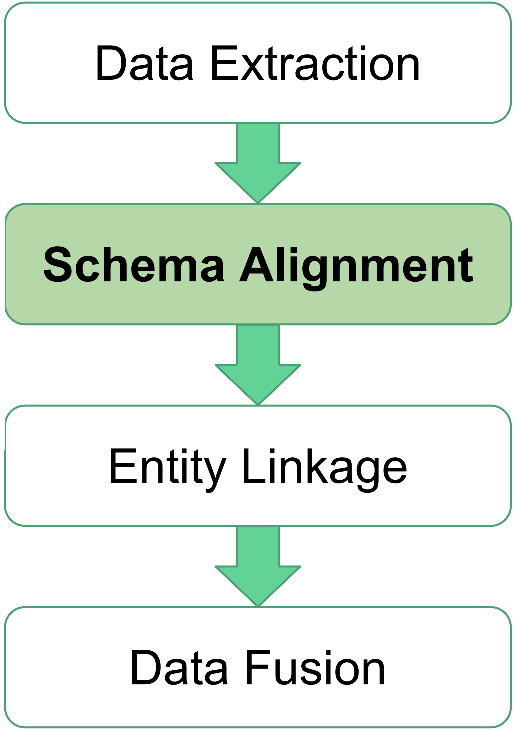
# Revisit: Recipe for Data Extraction

- Problem definition: **Extract structure from semi- or un-structured data**
- Short answers
  - **Wrapper induction has high prec/rec**
  - **Distant supervision is critical for collecting training data**
  - **DL effective for texts and LR is often effective for semi-stru data**

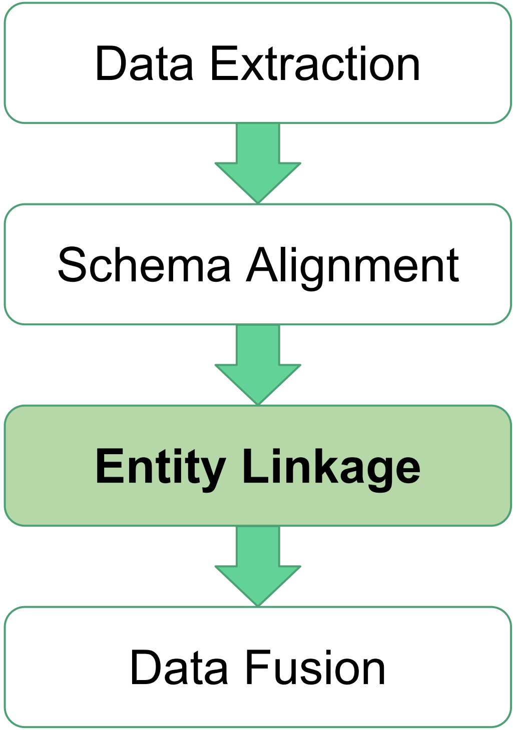
# Revisit: Recipe for Schema Alignment

- Problem definition: **Align attributes with the same semantics**
- Short answers
  - **Interactive semi-automatic mapping**
  - **DL-based universal schema revived the field**
  - **Combine schema matching and universal schema for future**

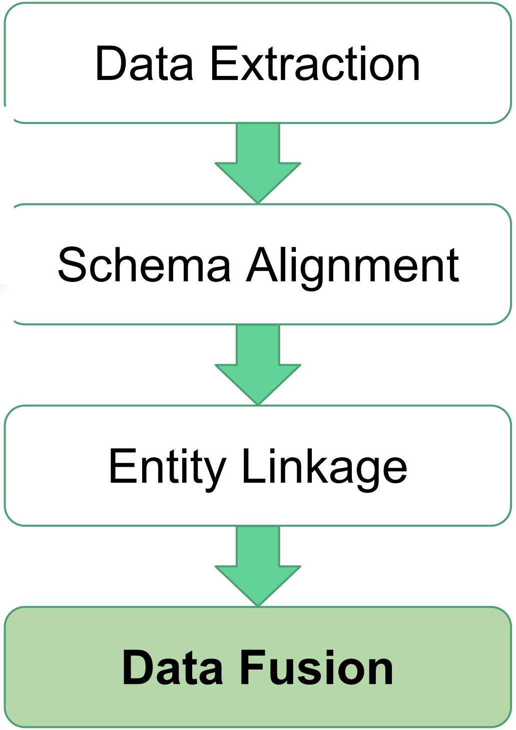
# Revisit: Recipe for Entity Linkage

- Problem definition: **Link references to the same entity**
- Short answers
  - **RF w. attribute-similarity features**
  - **DL to handle texts and noises**
  - **End-to-end solution is future work**

# Recipe for Data Fusion

- Problem definition: **Resolve conflicts and obtain correct values**
- Short answers
  - **Reasoning about source quality is key and works for easy cases**
  - **Semi-supervised learning has shown BIG potential**
  - **Representation learning provides positive evidence for streamlining data fusion.**

# DI and ML: A Natural Synergy

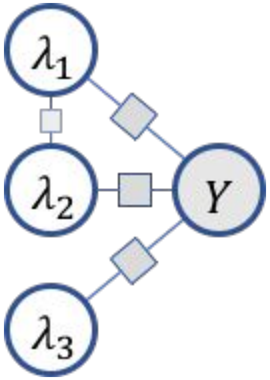
- Data is bottleneck of modern ML and AI applications

- DI-related methods and algorithms have revolutionized the way supervision is performed.
    - Weak supervision signals are integrated into training datasets

- Data integration solutions (e.g., data cataloging solutions) can lead to cheaper collection of training data and more effective data enrichment

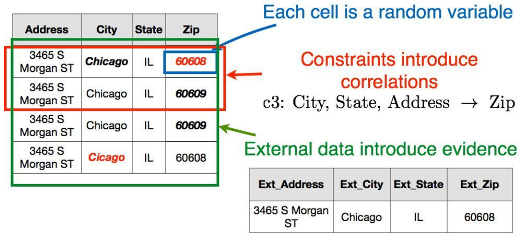
# Revisit: Recipe for Creating Training Data

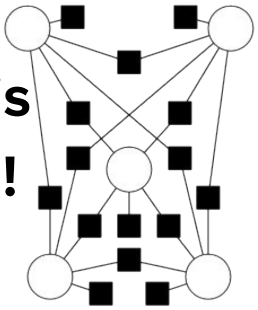
- Problem definition: **Go beyond gold labels to noisy training data.**
- Short answers
    - **Transition from “gold” labels to “high-confidence” labels.**
    - **Modeling error rates is key. The notion of *data source* is different.**
    - **Need for debugging tools, bias detection, and recommendations of weak supervision signals.**



# Recipe for Data Cleaning

- Problem definition: **Detect and repair erroneous data.**
- Short answers
    - **ML can help partly-automate cleaning. Domain-expertise is still required.**
    - **Scalability of ML-based data cleaning methods is a pressing challenge. Exciting systems research!**
    - **We need more end-to-end systems!**



# Opportunities for DI

**One System vs. An Ecosystem:** Every RBMS is a monolithic system. This paradigm has failed for DI. Tools for different DI tasks are prevalent. We need abstractions and execution frameworks for such ecosystems.

**Humans-in-the-loop:** DI tasks can be very complex. Is weak supervision the right approach to inject domain knowledge? What about quality evaluation?

**Multi-modal DI:** ML-based DI has focused on structured data with the exception of DI over images using crowdsourcing and some recent efforts that target textual data. DL is the de facto solution to reasoning about high dimensional data. Can is help develop unified DI solutions for visual, textual, and structured data?

**Efficient Model Serving:** This means efficient model serving. Many compute-intensive operations such as normalization and blocking are required. Featurization may also rely on compute-heavy tasks (e.g., computing string similarity). What is the role of pipelining and RDBMS-style optimizations?

# Opportunities for ML

**Data Catalogs:** Data augmentation relies on data transformations performed on data records in a single dataset. How can we leverage data catalogs and data hubs to enable data augmentation go beyond a single dataset?

**Valuable Data for ML applications:** Our community has focused on assessing the value of data [Dong et al., VLDB'12, Koutris et al., JACM 2015]. These ideas are not pervasive to ML but if ML is to become a commodity [Jordan, 2018] we need methods to reason about the value of data.

**DI for Benchmarks:** Increasing efforts on creating manually curated benchmarks for ML. Current efforts rely on manual collection and curation. How can we leverage meta-data and existing DI solutions to automate such efforts?

"How reliable are our current measures of progress in machine learning?"
*Do CIFAR-10 Classifiers Generalize to CIFAR-10?*, Ben Recht et al., 2018

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# DI & ML as Synergy

- **ML for effective DI: AUTOMATION, AUTOMATION, AUTOMATION**
  - Automating DI tasks with training data
  - Ensemble learning and deep learning provide promising solutions
  - Better understanding of semantics by neural network

- **DI for effective ML: DATA, DATA, DATA**
  - The software 2.0 stack is data hungry
  - Create large-scale training datasets from different sources
  - Cleaning of data used for training

Thank you!

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