

Using Scalable Inference to Build DeepDive: A Declarative Dark Data System.

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DeepDive

Dark Data System: ETL on Steroids

Quality that can exceed paid human
annotators and volunteers





DeepDive

Extraction, Integration, & Cleaning
are *inference problems*

Focus on what matters:
“Amdahl’s law” for quality





DeepDive

Declarative Inference:

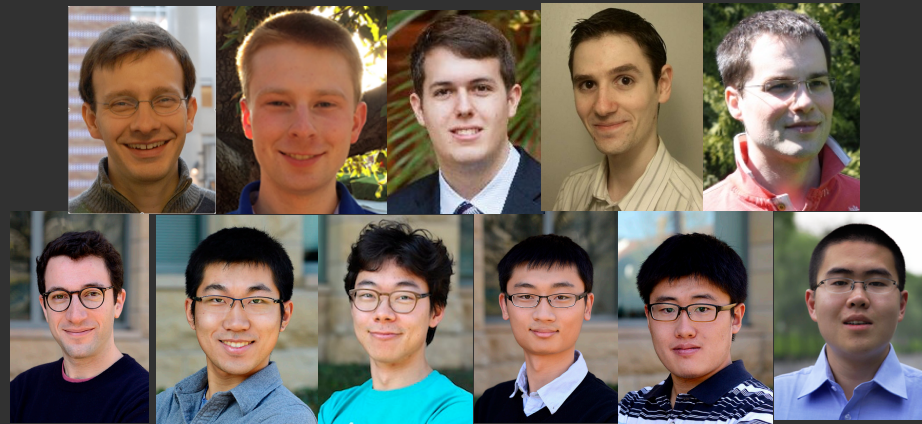
*Think about **features** not **algorithms**.*

Enables non-CS users, but
scale is a challenge.



First, some thank yous





The DeepDive Team

<http://deepdive.stanford.edu/>



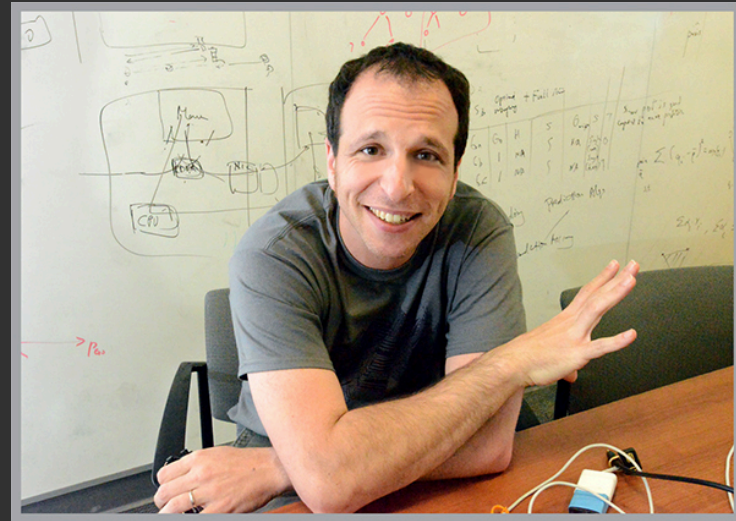
INCOMPLETE THANK YOU



Special Thank You to my optimization advisors



Stephen J. Wright
Wisconsin.
God of Optimization.



Ben Recht
Berkeley.
Patriots Fan.



My Actual Advisor



My Actual Boss



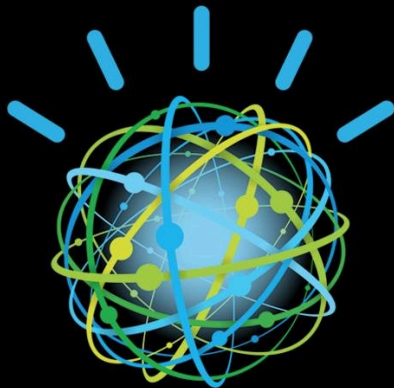
Many Existing Systems with the similar goal

Unstructured
Input

Structured
Knowledge
Base

Many Amazing Industrial Systems

IBM Research



An Incomplete Set of Awesome Research



TextRunner & ReVerb
(Washington)



NELL
(CMU)



Knowledge Vault
(Google)



ProbKB
(Florida)



Lixto



SystemT
(IBM)



YAGO-NAGA, SOFIE
(MPI)



DBLife, xLog
(Wisconsin)



StatSnowBall
(Tshinghua & MSRA)

Many
more



Back to our
regularly scheduled programming...



The world's scientific
knowledge is **accessible**,
but not **readable**.



Today, some pressing problems require **macroscopic knowledge**



Climate &
Biodiversity



Health



Financial
Markets



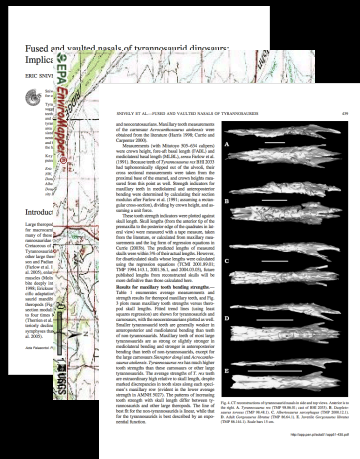
Could we build a machine
to **read** for us?



PaleoDeepDive

The Goal

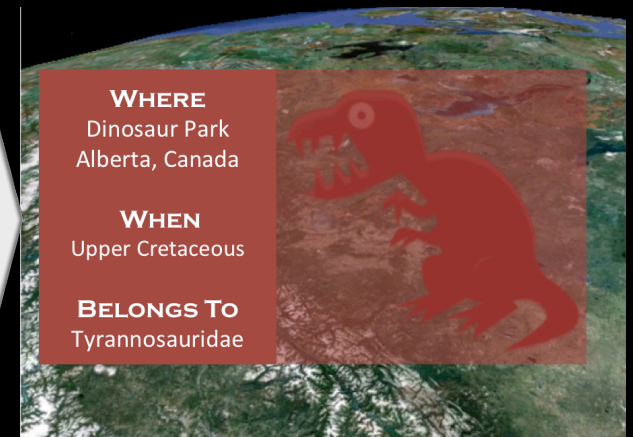
Extract paleobiological facts to build **high coverage** fossil record.



T. Rex are found dating to the upper Cretaceous.

Statistical Inference

Appears("T. Rex", "Cretaceous")

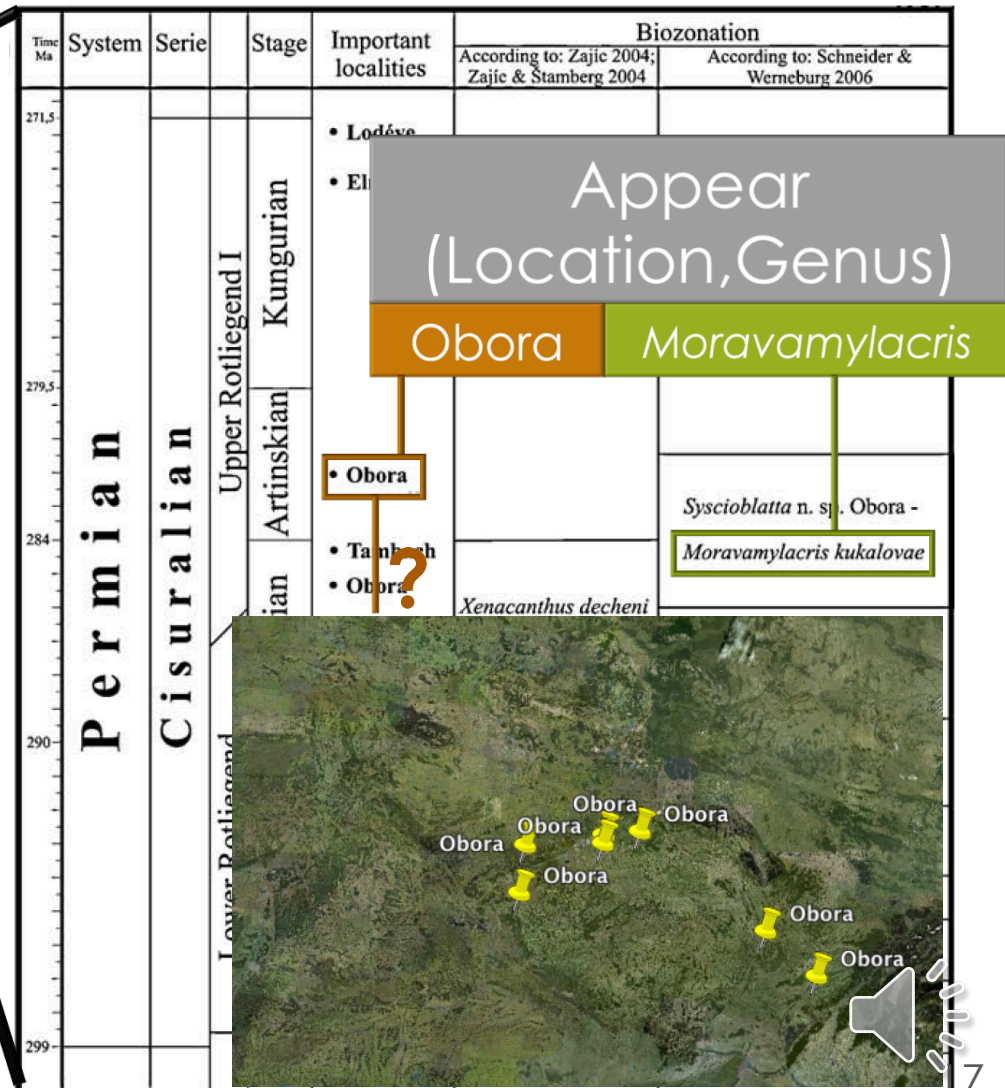
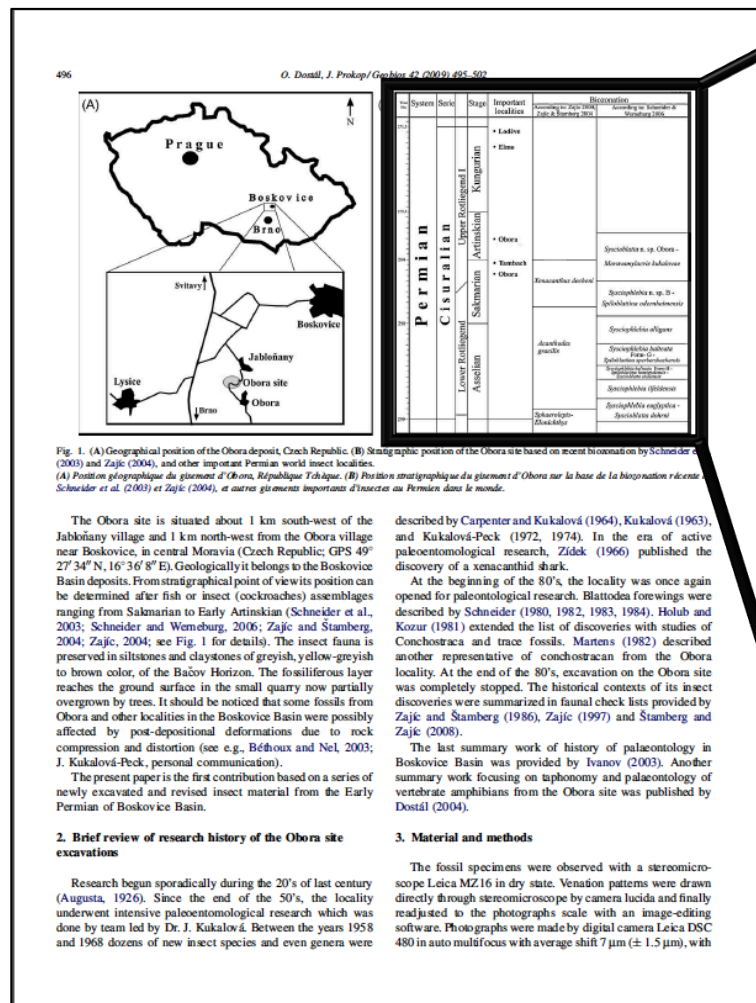


Aggressive Approach

Every character, word, part of speech is a variable
Statistical inference on billions of variables.



Data are buried in tables, but not in a self-contained way



Data are buried in tables, but not in a self-contained way

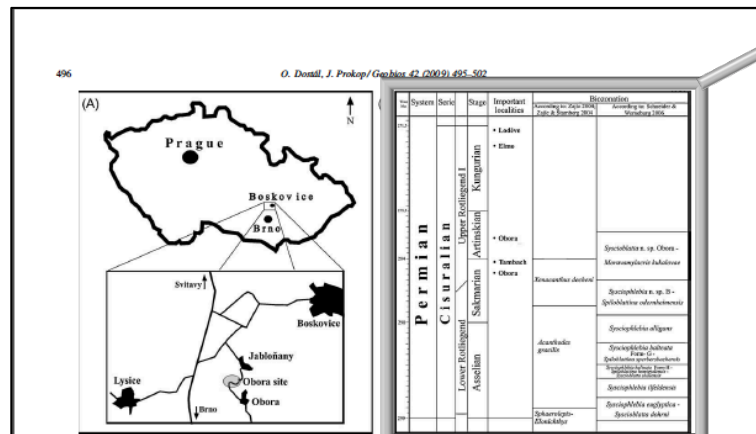


Fig. 1. (A) Geographical position of the Obora deposit, Czech Republic. (B) Stratigraphic position of the Obora site based on recent biostratigraphy by Schneider et al. (2003) and Zajíc (2004), and other important Permian world insect localities. (A) Position géographique du gisement d'Obora, République Tchèque. (B) Position stratigraphique du gisement d'Obora sur la base de la biostratigraphie récente de Schneider et al. (2003) et Zajíc (2004), et autres gisements importants d'insectes au Permien dans le monde.

The Obora site is situated about 1 km south-west of the Jablůňany village and 1 km north-west from the Obora village near Boskovice, in central Moravia (Czech Republic; GPS 49° 27' 34" N, 16° 36' 8" E). Geologically it belongs to the Boskovice Basin deposit. From stratigraphical point of view, its position can be determined after insect (coelocanthy assemblages ranging from Sakmarian to Early Artinskian (Schneider et al., 2003; Schneider and Wernberg, 2006; Zajíc and Štámbek, 2004; Zajíc, 2004; see Fig. 1 for details). The insect fauna is described by Carpenter and Kukalová (1964), Kukalová (1963), and Kukalová-Peck (1972, 1974). In the era of active paleontological research, Zidek (1966) published the discovery of a xenacanthid shark. At the beginning of the 80's, the locality was once again described by Schneider (1980). In 1981, Hladik and Kozur (1981) extended the list of discoveries with insects, Conchostraca and trace fossils. Martens (1982) described

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(Augusta, 1926). Since the end of the 50's, the locality underwent intensive paleontological research which was done by team led by Dr. J. Kukalová. Between the years 1958 and 1968 dozens of new insect species and even genera were

directly through stereomicroscope by camera lucida and finally readjusted to the photographs scale with an image-editing software. Photographs were made by digital camera Leica DSC 480 in auto multifocus with average shift 7 µm (± 1.5 µm), with

Time Ma	System	Serie	Stage	Important localities	Biozonation	
					According to: Zajíc 2004; Zajíc & Štámbek 2004	According to: Schneider & Wernberg 2006
271.5	Permian	Cisuralian	Upper Rotliegendes I	• Loděv		
				• El		
279.5						
284						
	Permian	Artinskian	Kungurian			
299	Permian	Artinskian	Kungurian			

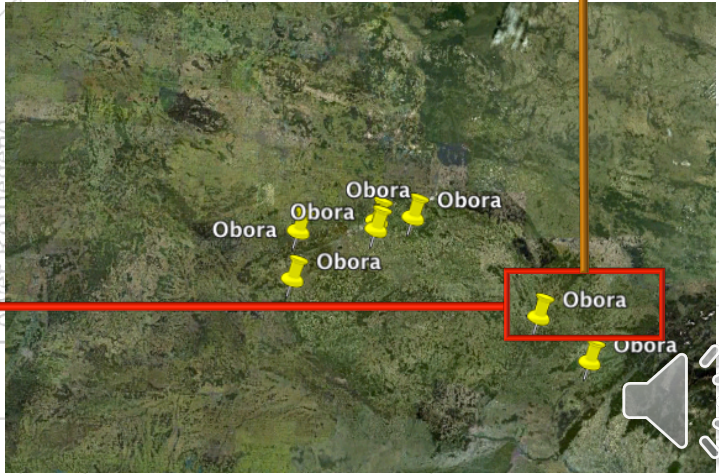
Appear
(Location, Genus)
Obora Moravamylacris

Obora

Obora?

Sysciobiata sp. Obora -
Moravamylacris kukalovae

Xenacanthus decheni



Joint Probabilistic Inference Matters.



PaleoDeepDive



Shanan Peters (Geo) and Miron Livny (CS)
DeepDive.Stanford.edu (**Ce Zhang** et al.)

PaleoDB

Human-created

 329 volunteers

 13 years

 46K documents

200+ Papers,
17 Nature/Science

Formation
Precision

PaleoDB Volunteers: **0.84**

PaleoDeepDive: **0.94**

Peters, S., Zhang, C, Livny, M., and Ré, C. A New Machine-Aggregated Empirical History of Life on Earth. **PLOS ONE**, 2014 featured in **Nature** July 1, 15



PaleoDeepDive

Machine-created

10x documents.

100x extractions.

Preliminary Precision

Hope: knowledge bases can
help **accelerate science.**



Tree of Life



Drug Repurposing



Genomics

*Used by a number of companies with quality
that best **professional** human annotators;
winner of TACKBP14.*



Human Trafficking on the (Dark) Web...



MEMEX

Hypothesis: Trafficked individuals offer **lower cost** and **riskier** sexual services.

In Plain sight: Web ads for such services

Challenges:

1. Need **high-resolution information** to build model.
 - *services for what rate, ethnicity, location, etc.*
2. Scientific papers are **clear**—dark web is **obfuscated**.



Human Trafficking on the (Dark) Web...



Web
Text



VIDA
Where data comes to life

db DeepDive

Structured Info: Phone #,
Rates of Service, ...

Normal two call agency. Jessica was ready when I arrived at body. A couple of tattoos but not in visual-annoying locations pleasing the client - definitely not GFE. She does the basics. recommending - I may repeat but only because of her looks.

Drug_Abuse?
Forced_Prostitution?

Use: law enforcement/ NGOs



In Use by Law Enforcement



*New York DA use MEMEX Data for all trafficking investigations this year. **Real Arrests***

For DARPA MEMEX, we were operational in 6 months

- ▣ Processed >35M documents (~26M records)
- ▣ Tens of columns (location, phone #, price, etc)
- ▣ With compute times of less than a day
- ▣ >90% Precision for most relations

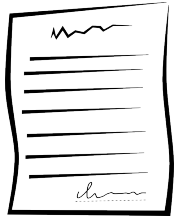


Declarative language allows
algorithmic independence



Example: Extracting Spouse Relations

Corpus (Dark Data)



U.S. President **Barack Obama**'s wife **Michelle Obama** honored all mothers on Mother's Day and offered her thoughts ...

How do we produce tuples like

`Married(Barack Obama, Michelle Obama)`

And all other married couples in text?

Examples on Github!



0. Data Preprocessing

Corpus (Dark Data)



text

U.S. President Barack Obama's wife Michelle Obama honored all mothers on Mother's Day and offered her thoughts ...

DDlog: Declarative inspired by Datalog, MLNs

```
Sentences :- !nlp(Corpus).  
function nlp over (text)  
    returns (words,pos,ner,sid)  
    implementation "udf/corenlp.sh ..." .
```

Sentences

words	POS	NER	SID
[U.S.,President,Barack,Obama,'s,wife,Michelle,Obama,...]	[NNP,NNP,NNP,NNP,POS,NN,NNP,NNP,...]	[LOC,O,PER,PER,O,O,PER,PER,...]	S1

1. Candidate Mappings

Sentences

words	POS	NER	SID
[U.S.,President,Barack,Obama,'s,wife,Michelle,Obama,...]	[NNP,NNP,NNP,NNP,POS,NN,NNP,NNP,...]	[LOC,O,PER,PER,O,O,PER,PER,...]	S1

Mentions :- !ext_person(Sentences).

```
function ext_person over (words,pos,ner,sid)
    returns (sid,mid,words)
implementation "udf/find_person.py".
```

MarriedCandidate(s,p1,p2) :-
Mentions(s,p1,_), Mentions(s,p2,_).

Mentions

SID	MID	words
S1	M1	[Barack,Obama]
S1	M2	[Michelle,Obama]

MarriedCandidate

SID	MID	MID
S1	M1	M2

2. Feature Extraction

Sentences

words	POS	NER	SID
[U.S.,President,Barack,Obama,'s,wife,Michelle,Obama,...]	[NNP,NNP,NNP,NNP,POS,NN,NNP,NNP,...]	[LOC,O,PER,PER,O,O,PER,PER,...]	S1

Features :- !ext_features(Sentences, MarriedCandidate).
function ext_features ...
implementation "udf/ext_features.py".

Mentions

SID	MID	words
S1	M1	[Barack,Obama]
S1	M2	[Michelle,Obama]

MarriedCandidate

SID	MID	MID
S1	M1	M2

Features

MID	MID	feature
M1	M2	's wife

3. Inference Rules

Sentences

words	POS	NER	SID
[U.S.,President,Barack,Obama,'s,wife,Michelle,Obama,...]	[NNP,NNP,NNP,NNP,POS,NN,NNP,NNP,...]	[LOC,O,PER,PER,O,O,PER,PER,...]	S1

```
Married(p1,p2) :-
    MarriedCandidate(_,p1,p2),
    Features(p1,p2,f)
weight = f.
```

Just defined a
Binary classifier!

Married is an (incomplete) set of examples

Mentions

SID	MID	words
S1	M1	[Barack,Obama]
S1	M2	[Michelle,Obama]

MarriedCandidate

SID	MID	MID
S1	M1	M2

Features

MID	MID	feature
M1	M2	's wife



Users write Features & Transformation in **DDlog** (Inspired by MLNs) & Python.

```
Sentences :- !nlp(Corpus).
function nlp over (text) returns (words,pos,ner,sid)
    implementation "udf/corenlp.sh ..." .

Mentions :- !ext_person(Sentences).
function ext_person over (words,pos,ner,sid) returns (sid,mid,words)
    implementation "udf/find_person.py".
MarriedCandidate(s,p1,p2) :- Mentions(s,p1,_), Mentions(s,p2,_).

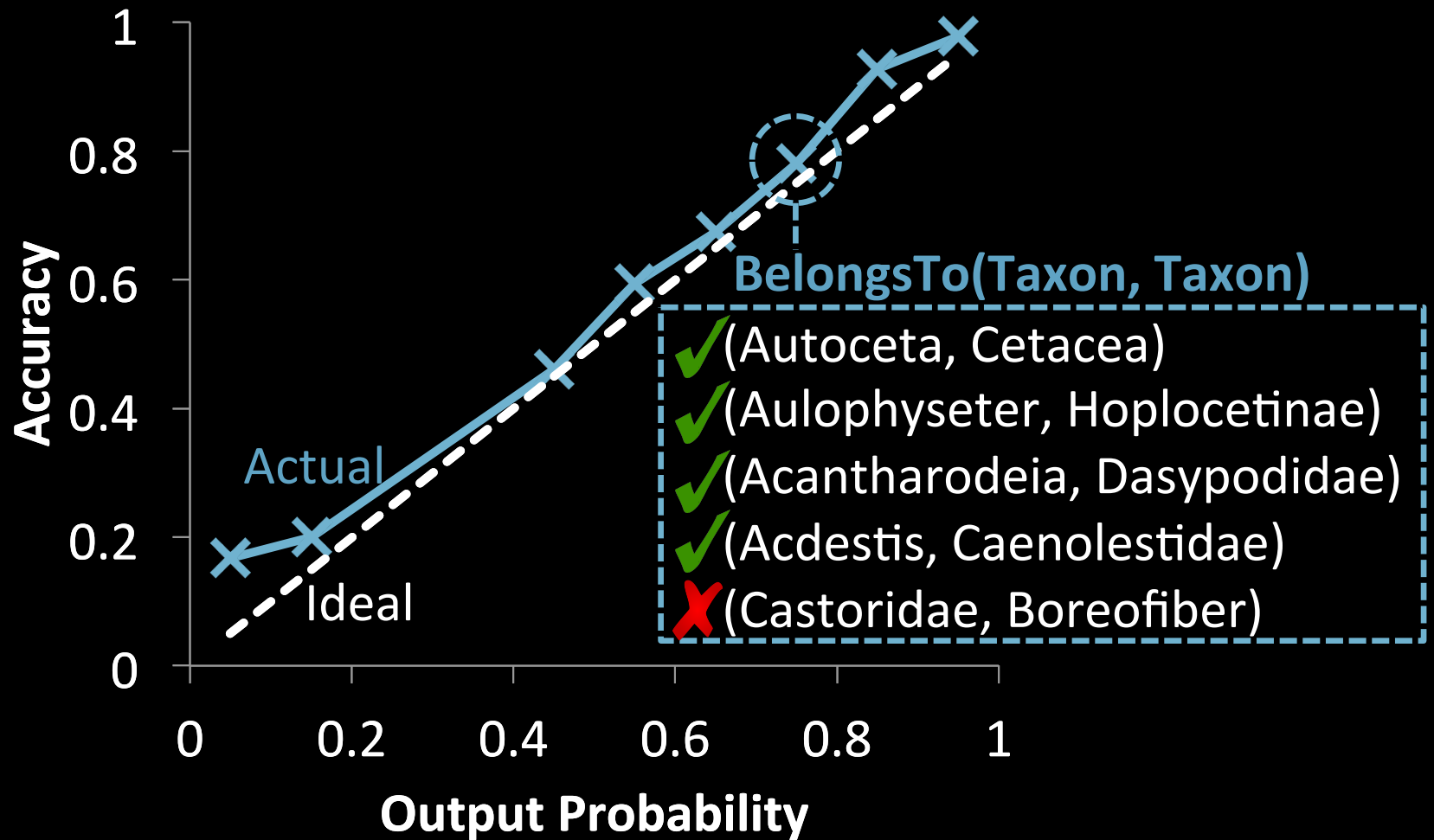
Features :- !ext_features(Sentences, MarriedCandidate).
function ext_features ... implementation "udf/ext_features.py".

Married(p1,p2) :- MarriedCandidate(_,p1,p2), Features(p1,p2,f)
weight = f.
```

No reference to algorithms: Just features.
DD does the rest. (*Demos online*)



Meaningful probability, not just scores



Algorithmic Independence

Define the *meaning*
independently of *the*
algorithm used to compute it.

algorithmic independences,
requires a *fast* engine....



The Key Balance



Key Issue: Balance
Statistical versus Hardware
Efficiency.



Statistical Analytics Crash Course

Staggering amount of machine learning/stats can be written as:

$$\min_x \sum_{i=1}^N f(x, y_i)$$

N (number of y_i s, data) typically in the billions
Ex: Classification, Recommendation, Deep Learning.

De facto iteration to solve large-scale problems: **SGD**.

$$x^{k+1} = x^k - \alpha N \nabla f(x^k, y_j)$$

Select one term, j , and estimate gradient.

Billions of tiny iterations.

How do we run SGD in Parallel?

Data Systems Perspective of SGD.

$$x^{k+1} = x^k - \alpha N \nabla f(x^k, y_j)$$

Insane conflicts: Billions of tiny (~100 instructions) jobs, RW conflicts on x , which is called **the model**.

How can we hope to speed this up with parallelism?

Serializability seems hopeless...

How do we run SGD in Parallel?

Thm: If we do ***no locking***, SGD still converges to right answer—at essentially the same theoretical rate!

Hogwild! [Niu, Recht, Ré, Wright NIPS11]

AsySCD [Liu, Wright et al. ICML14, JMLR14]

Buckwild! [DeSa et al. ICML15]

Technical conditions on ratio of processors, delays, (semantic) sparsity.

High-level idea: Go Hogwild! answer is only *statistically* correct.

Cortana & Project Adam

Microsoft's Digital Assistant

AI breakthrough: Microsoft's 'Project Adam' identifies dog breeds, points to future of machine learning



WIRED

"...using a technology called, of all things, Hogwild!"

I ♥ Microsoft®

<http://www.wired.com/2014/07/microsoft-adam/>

<http://www.geekwire.com/2014/artificial-intelligence-breakthrough-microsofts-project-adam-identifies-dog-breeds/>



A larger trend?

***NB:** There is theory here SGD [NIPS11,NIPS12], SCD [ICML14,ICML15], more soon and systems work [SIGMOD13, SIGMOD14, VLDB14]

Relaxing **consistency** to be **architecturally aware** can be a big performance win.

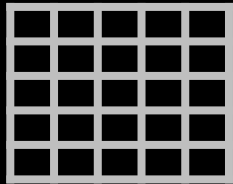


Dark(er) Data Systems

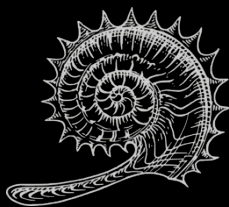
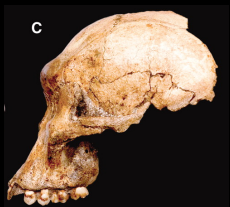


Integrative: Varied Data

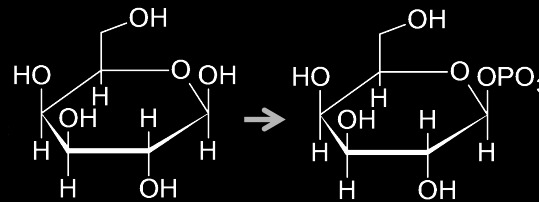
Text&Tables



Images



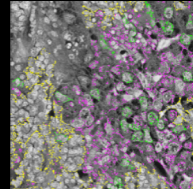
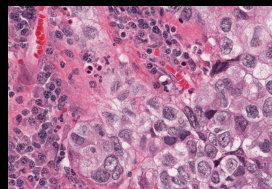
Diagrams



Taxonomy



Imaging



Drug
Repurposing

Paleobiology

Cancer
Imaging



Everyone: Broadly Usable

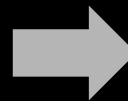
PaleoDeepDive



2 years



1 CS Student



PharmaDeepDive



6 months



1 BioE Student

How do we make building a KB
easier and cheaper?



Think about **features**, not **algorithms**.

A **framework** for feature engineering.

[SIGMOD14: train 100 models as quickly as 1]



Conclusion

1. Dark Data to help with **macroscopic questions**
2. Probabilistic inference = **algorithmic** independence
3. Hardware v. Statistical Efficiency.

