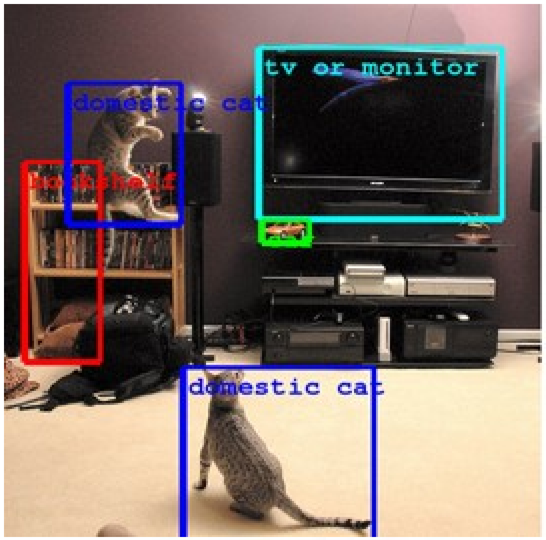
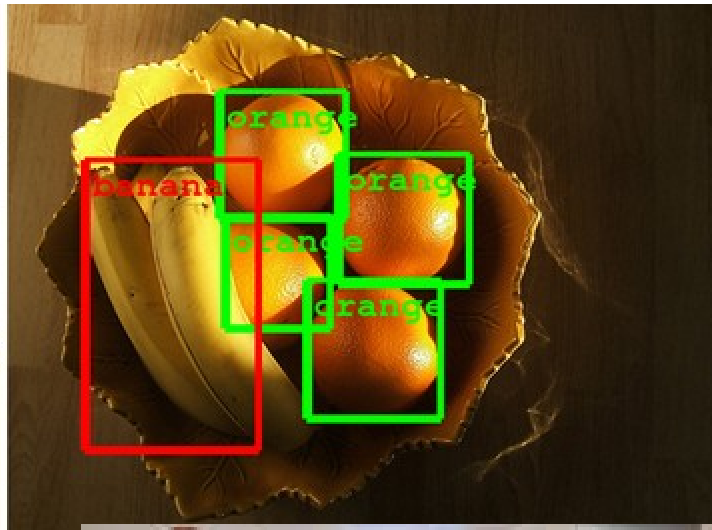
CS181: Introduction to Machine Learning

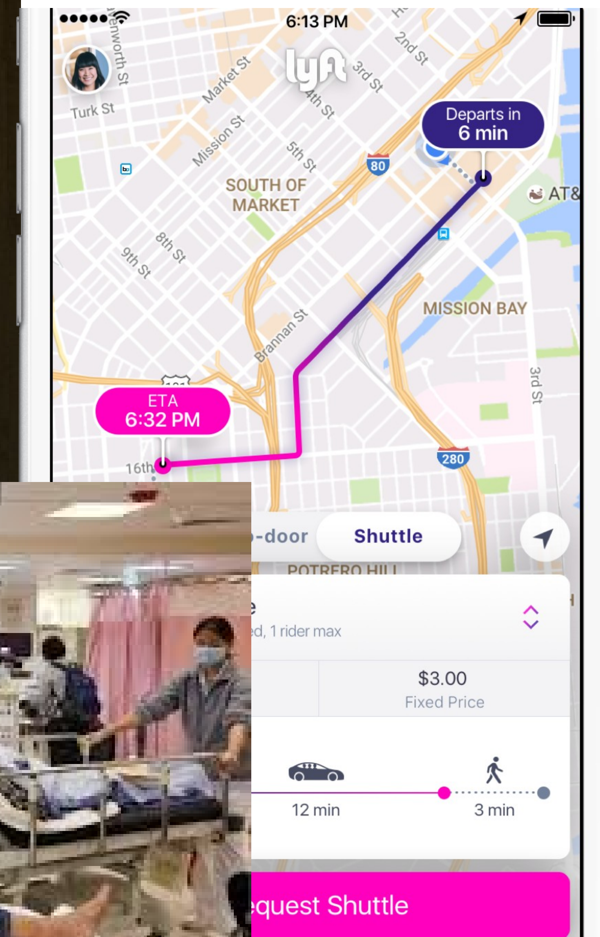
Finale Doshi-Velez

Staff: Jambay Kinley (head TF), Lev Grossman, Jason Ren, Michael Wornow, Alex Chin, Bill Zhang, Jason Huang, Jeffrey He, Jenny Huang, Catherine Zeng, Nari Johnson

What this course is about







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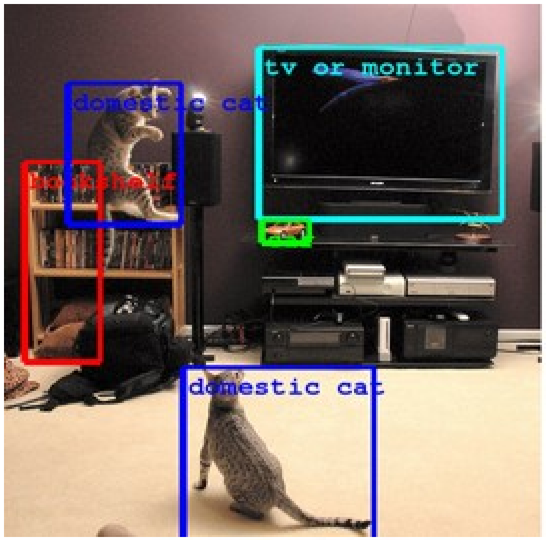

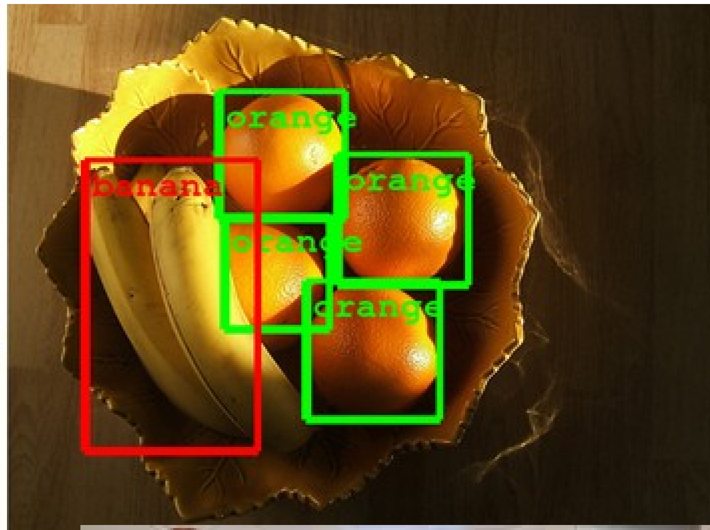

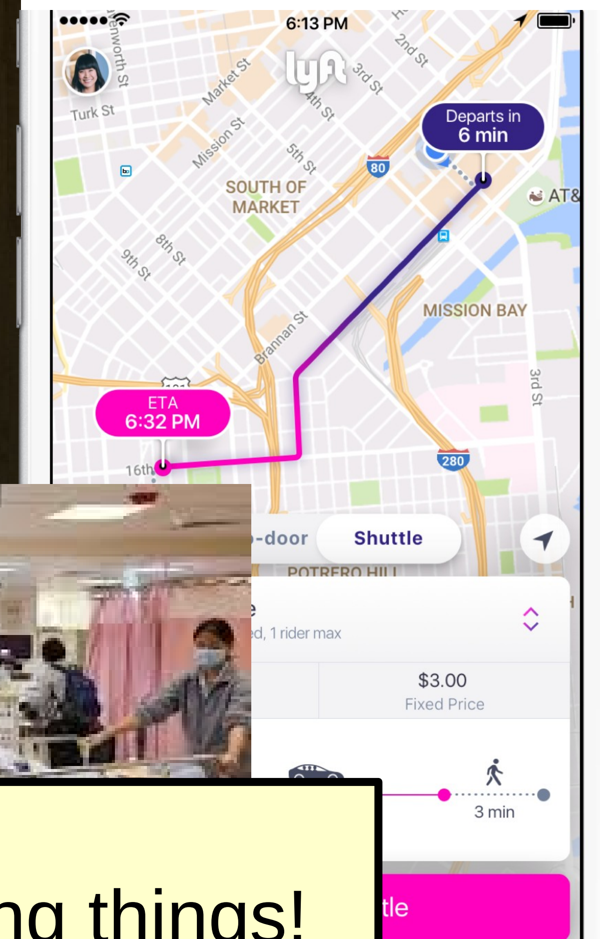

We can build the most amazing things!

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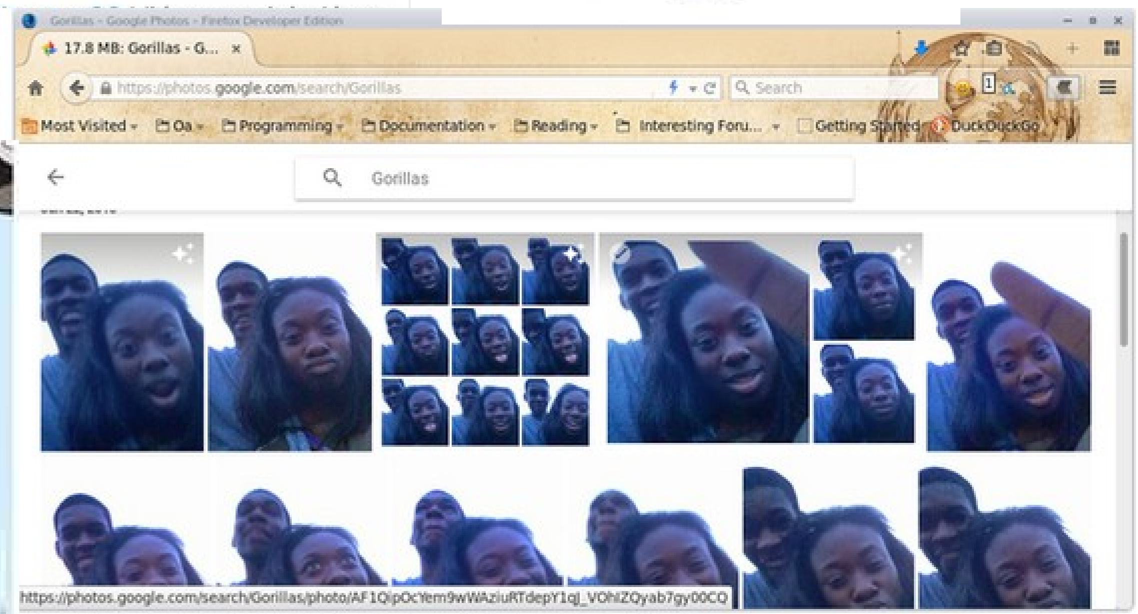

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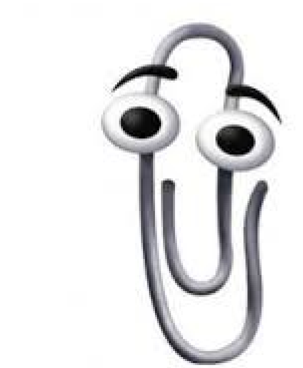

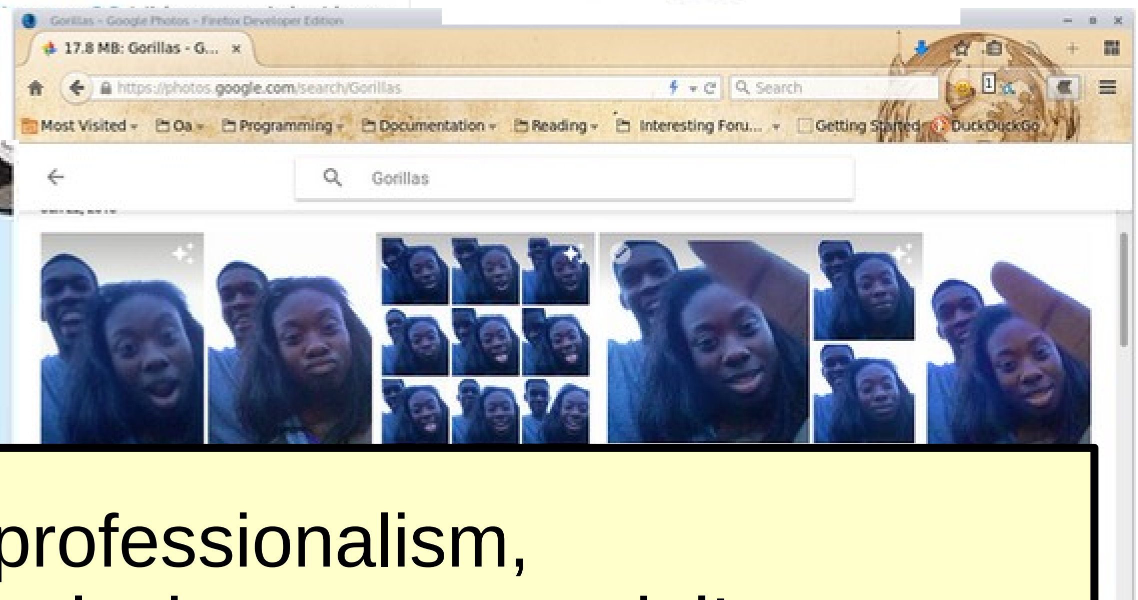

Rigor, professionalism,
ethics, and inclusion are essential!

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How we will get there

- Make appropriate model choices
- Have sufficient understanding to learn and apply the new techniques
- Identify sources of error
- Evaluate carefully

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- Make appropriate model choices
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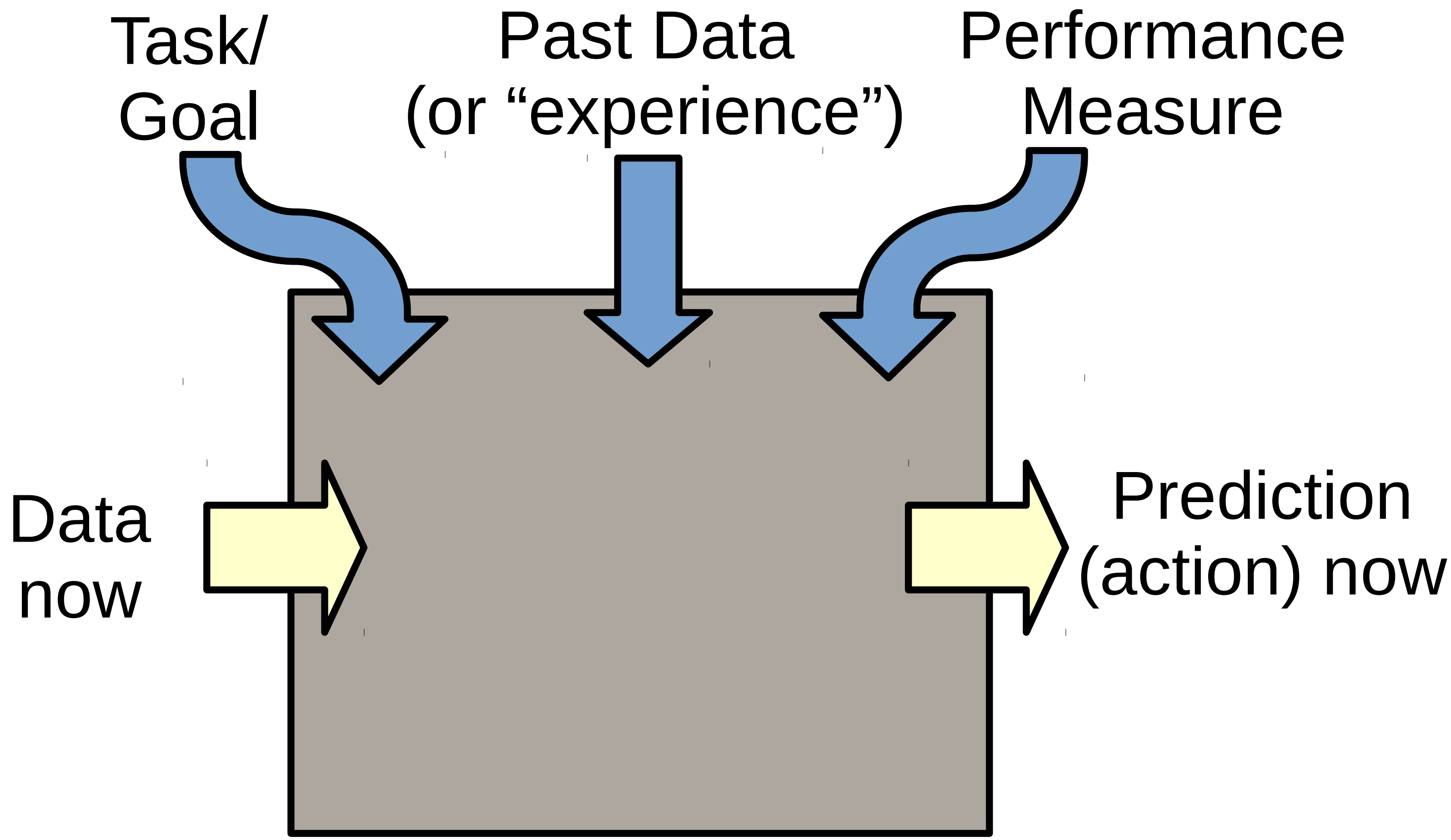
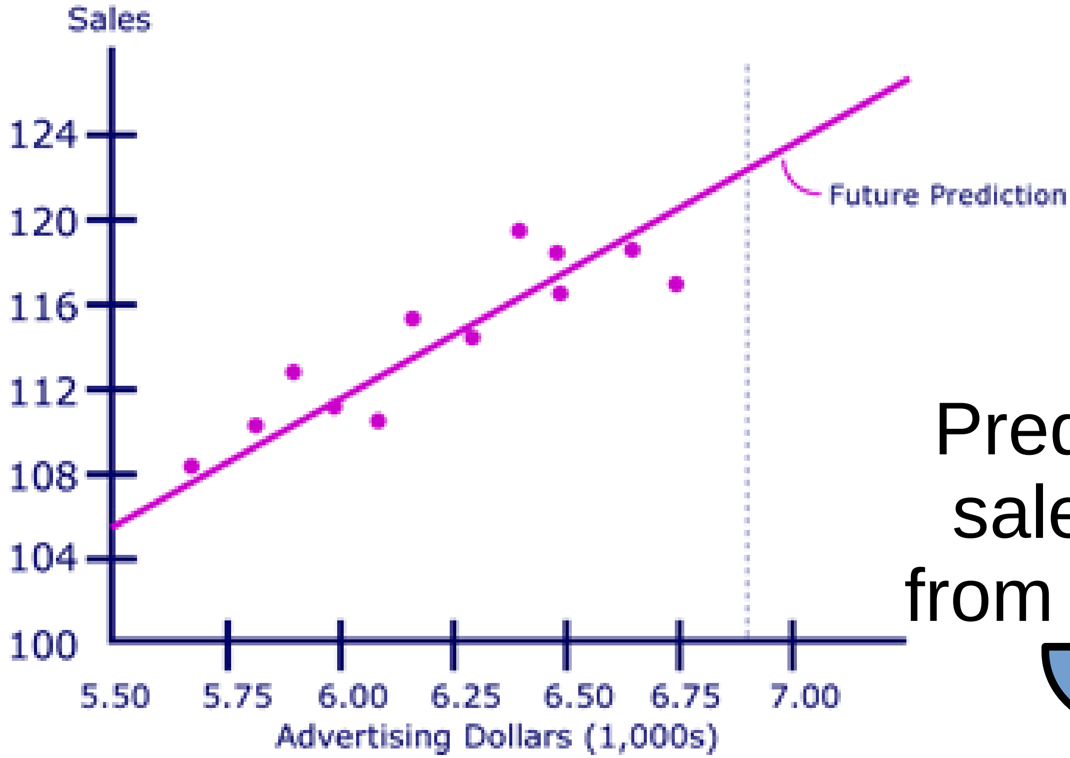
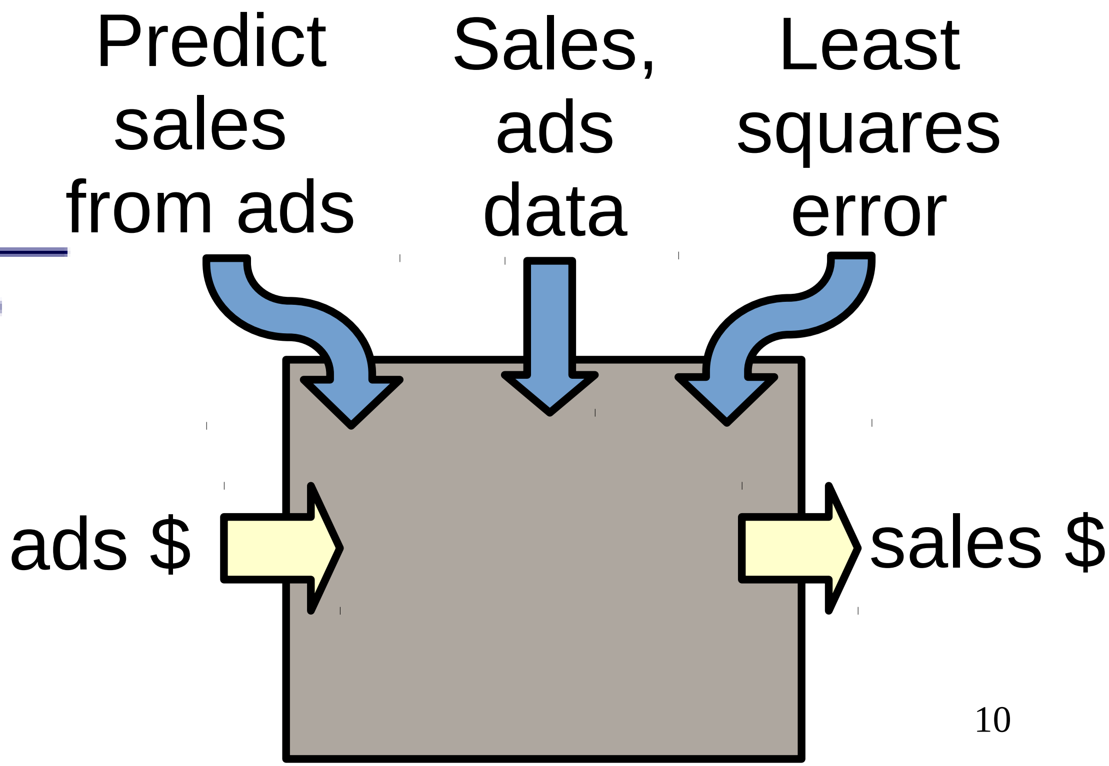
Let's get to it!

What is machine learning?



The starting point...





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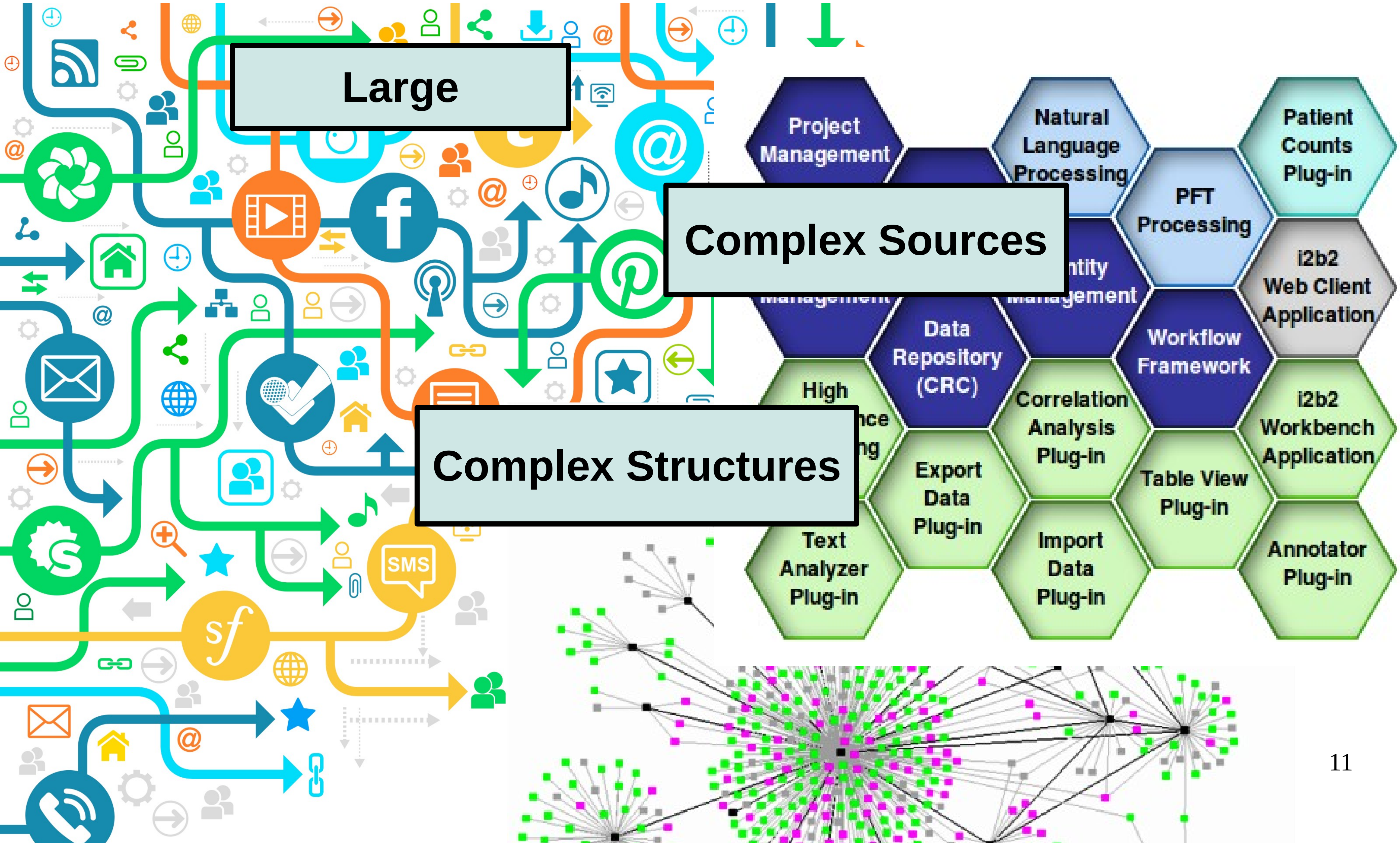
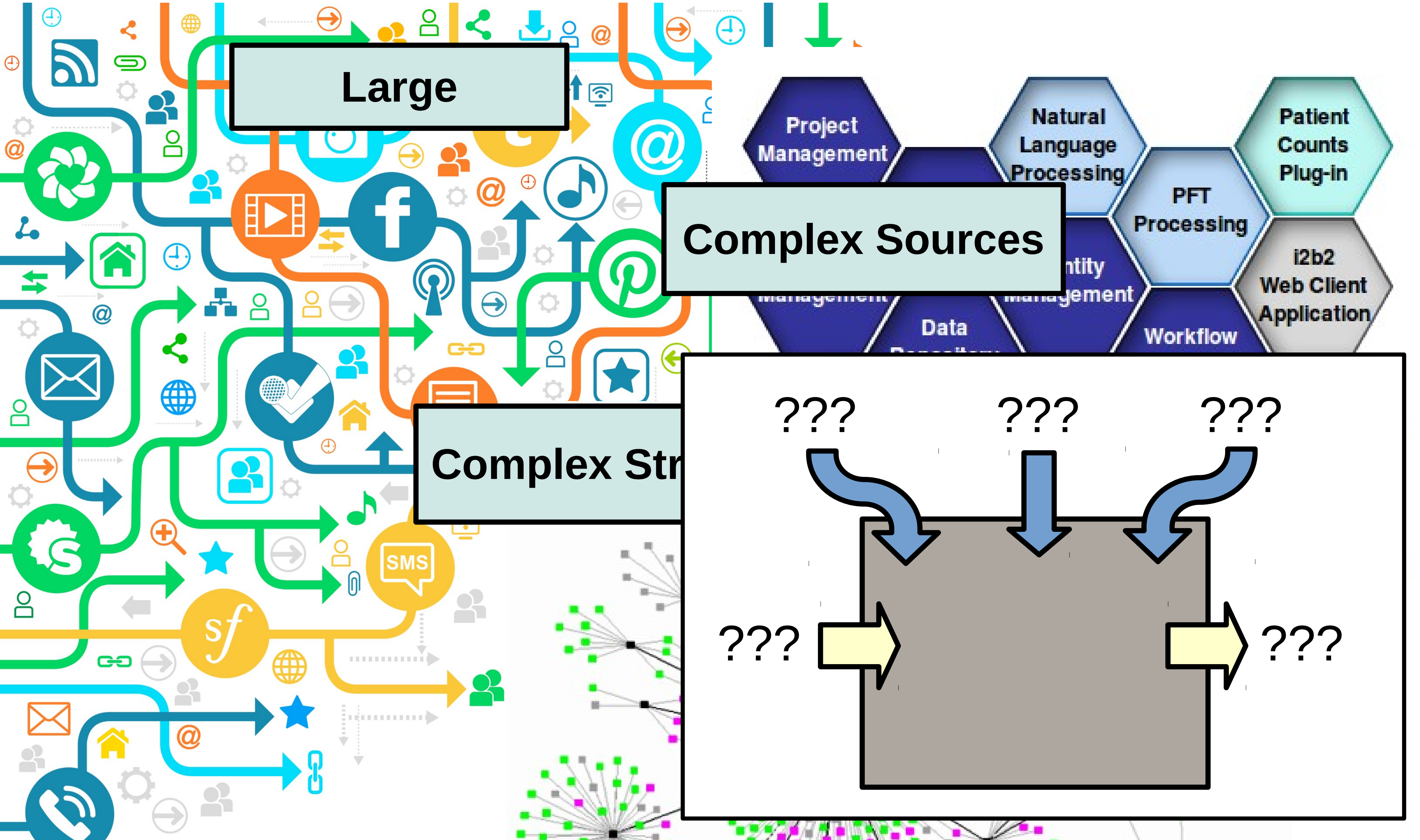
… where we are now



… where we are now



A Story:
Treating
Depression

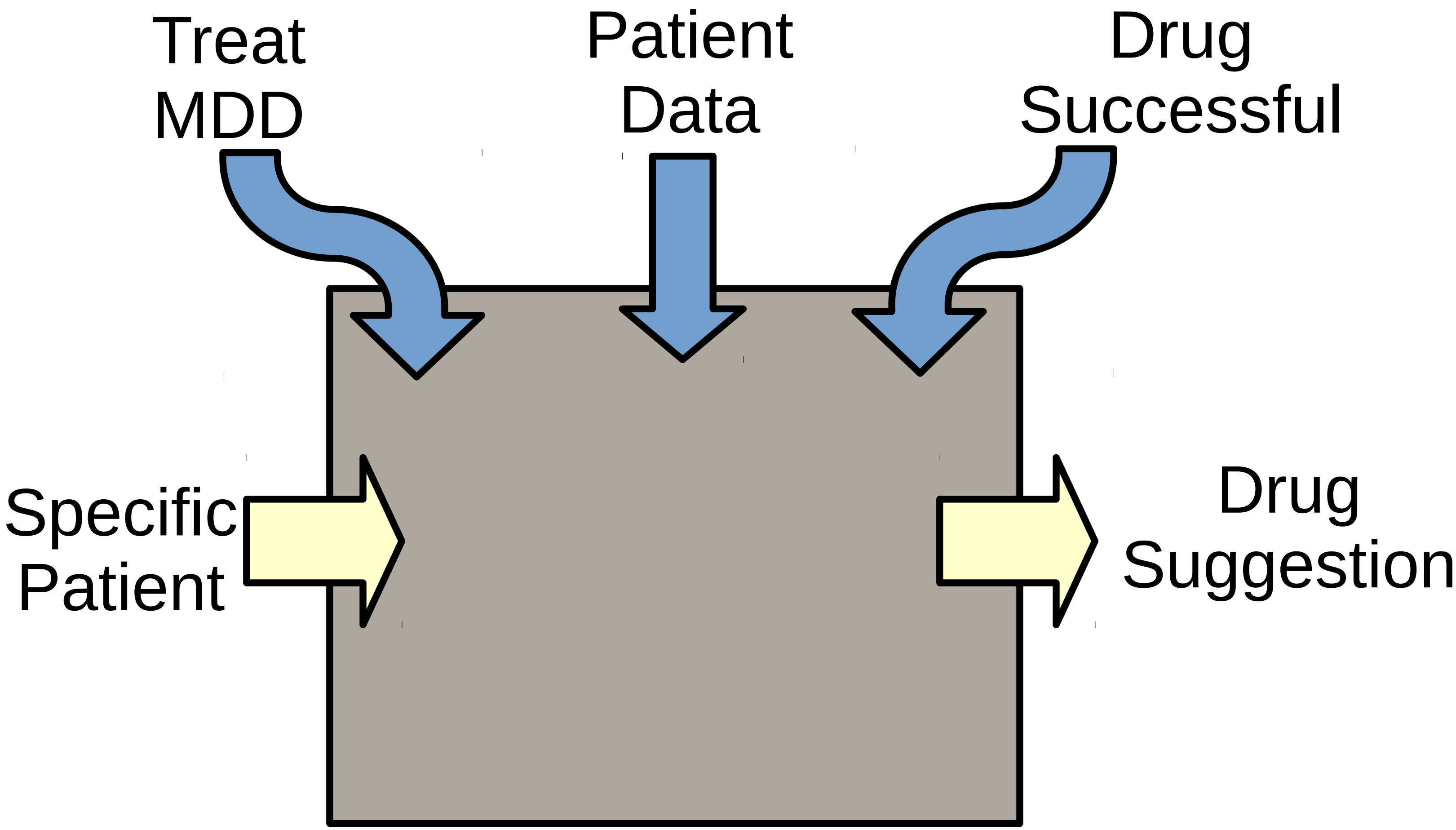
Clinical Question: What meds to give what depression patients?

Clinical Question: What meds to give what depression patients?

Clinical Question: What meds to give what depression patients?

Also: Can we explain who responds to what drug?

Formalizing...



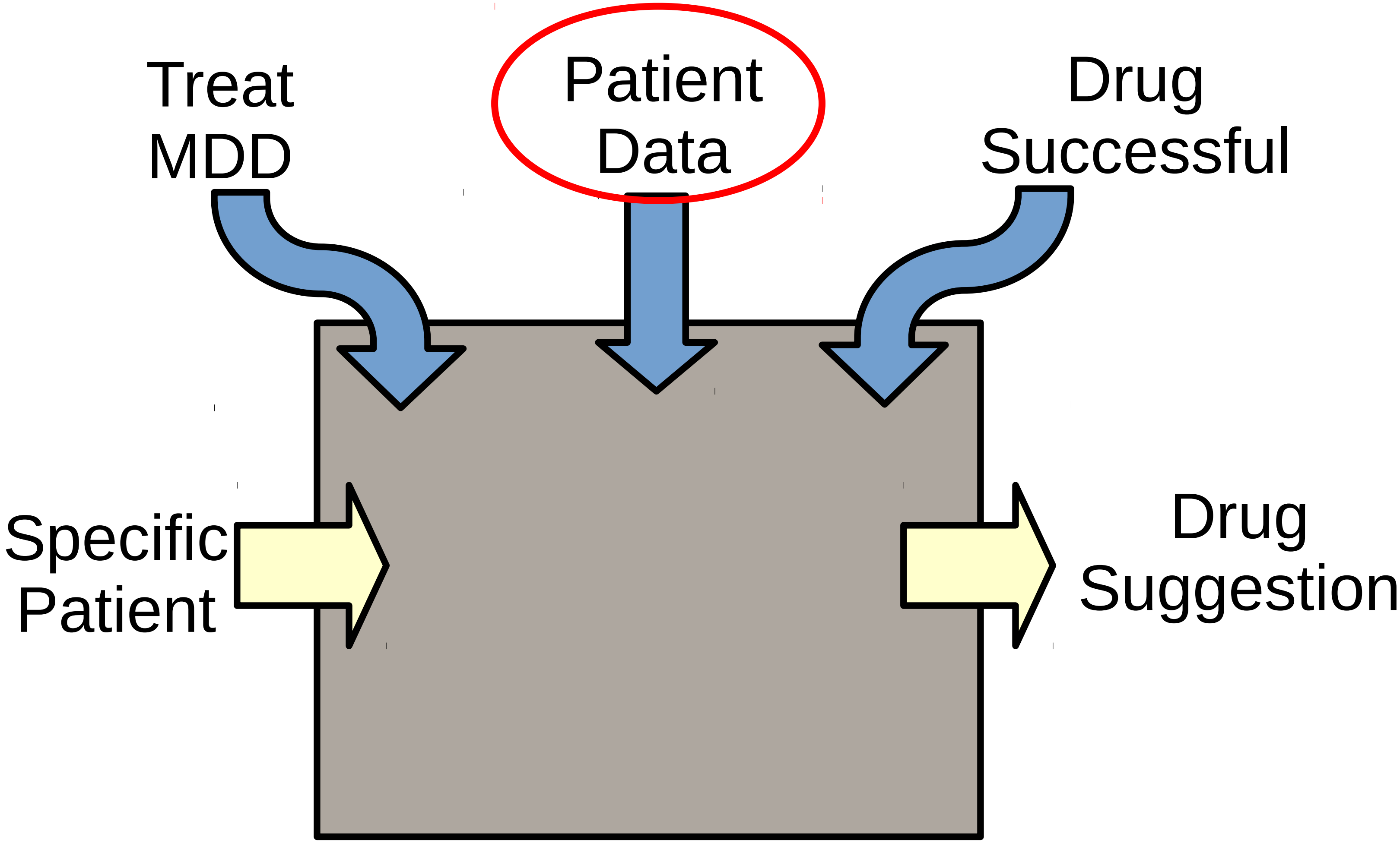
Current Approaches

Most current studies ask narrow questions and require specialized data. Examples:

- Large-scale clinical trial (STAR*D, COMED, iSPOT-D) analyses to decide between certain features or pairs of drugs (e.g. Chekroud et al., Joyce et al., Lavretsky et al.)
- MRIs and biomarkers to determine subtype and treatment choice (e.g. Liston et al., Craighead et al., Breitenstein et al.)

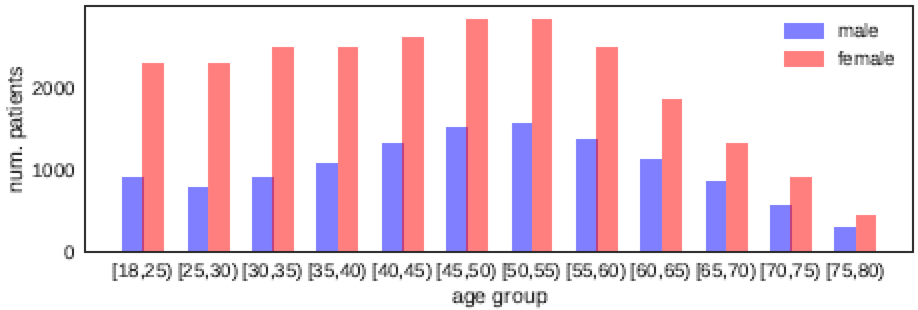
Our goal: We want to be able to recommend all common drugs, for patients with any prior treatment history.

Formalizing...



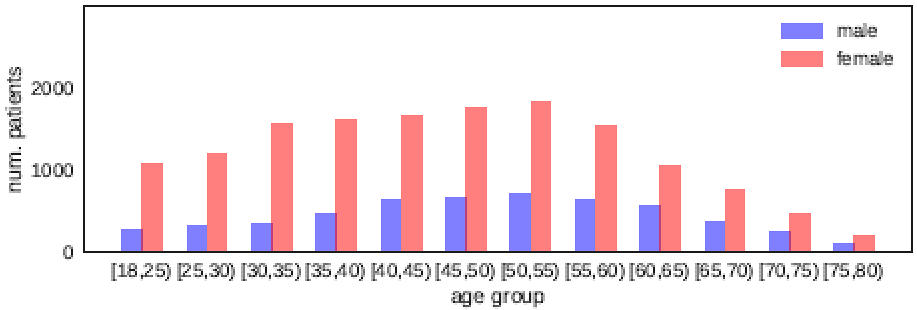
Cohort Statistics

Site A



	female	male	total	frac.
Asian	603	222	825	0.022
Black	959	412	1371	0.037
Hispanic	1006	402	1408	0.038
Other	2153	885	3038	0.082
White	20158	10415	30575	0.822
total	24879	12336	37217	
frac.	0.668	0.331		

Site B



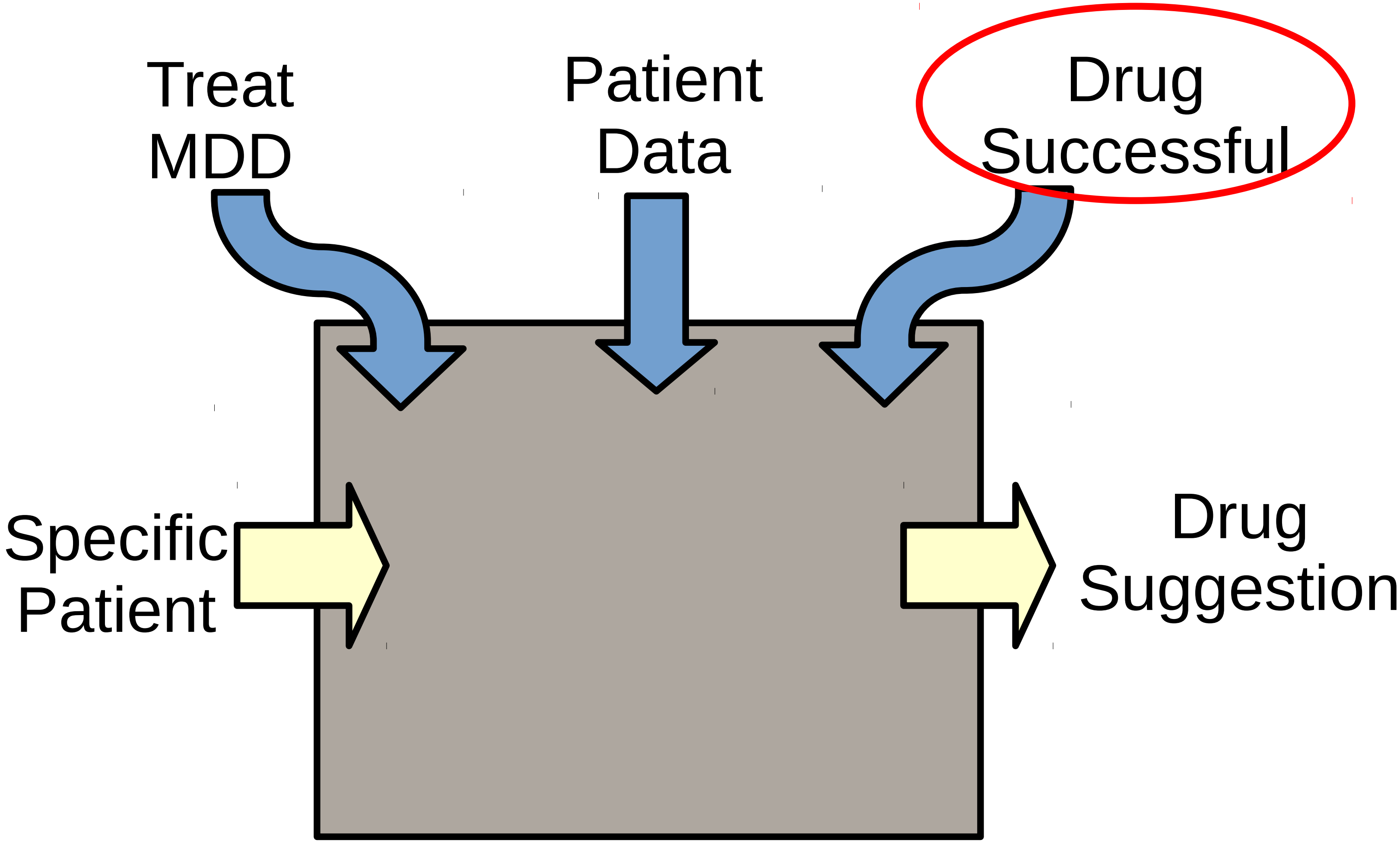
	female	male	total	frac.
Asian	233	56	289	0.014
Black	1604	419	2023	0.100
Hispanic	2264	657	2921	0.145
Other	1026	386	1413	0.070
White	9662	3888	13551	0.671
total	14789	5406	20197	
frac.	0.732	0.268		

Featurization

- Of the 22,000 unique codes (ICDs, CPTs, RXNORM) in the EHR, retain 7,291 which occur in at least 1,000 distinct patients.
- Focus on 10 primary drugs that are prescribed in at least 1000 patients

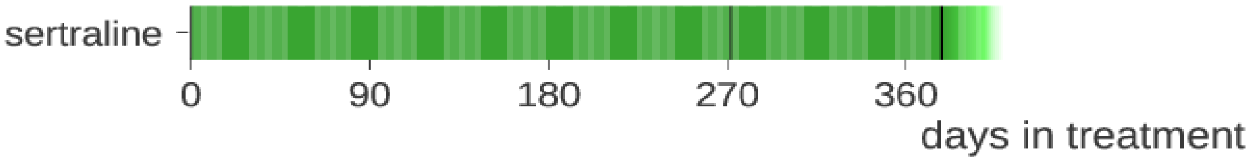
nortriptyline	sertraline	mirtazapine
amitriptyline	paroxetine	citalopram
bupropion	venlafaxine	escitalopram
fluoxetine		

Formalizing...

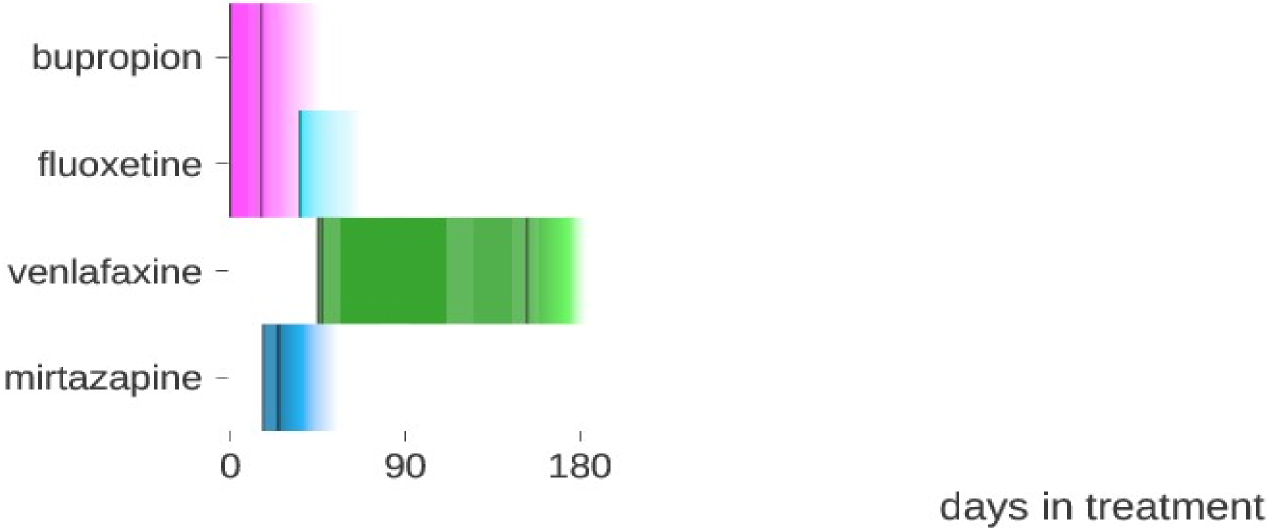


Performance Metric

"Instant Success" Patient

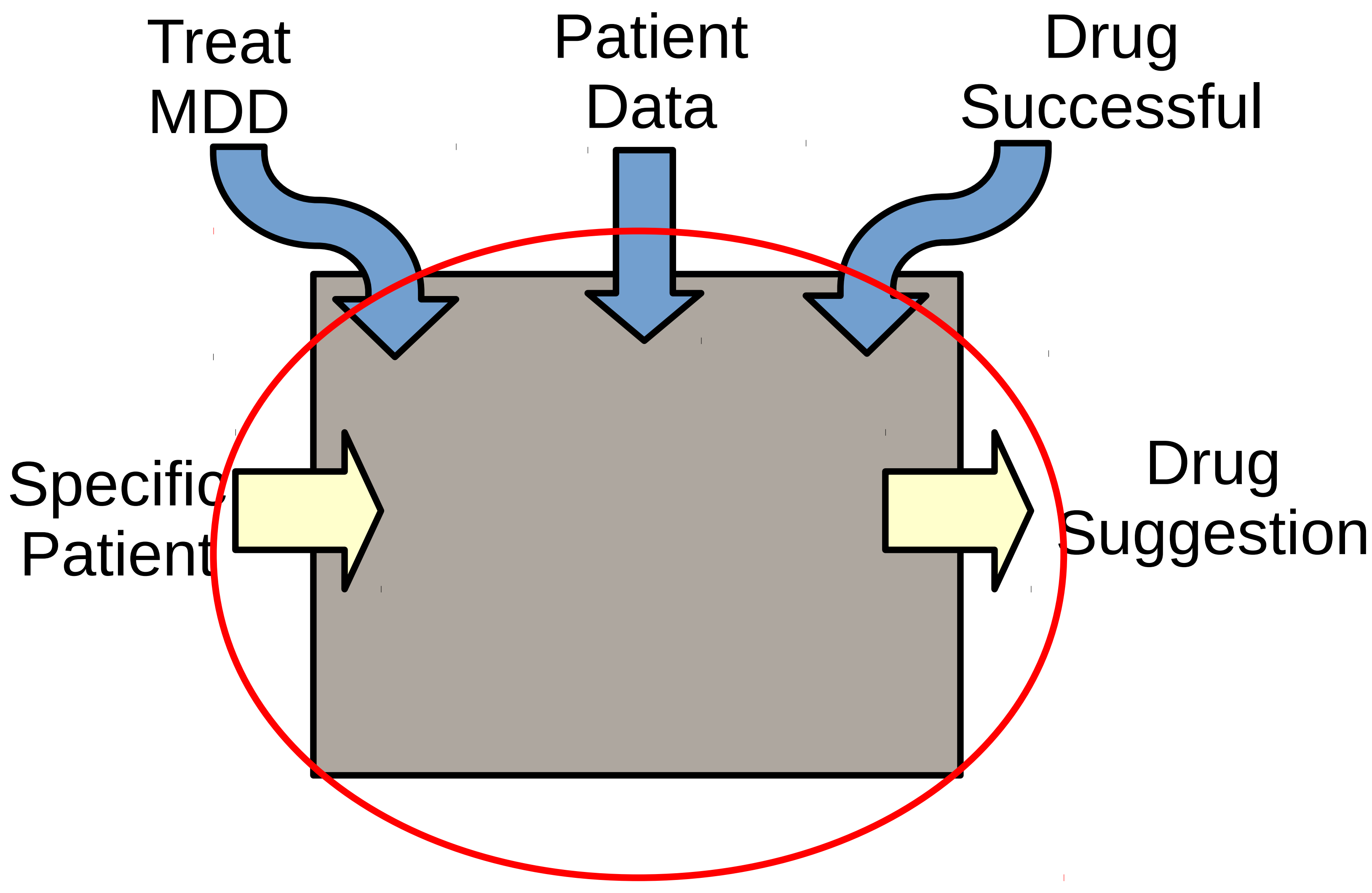


"Eventual Success" Patient



Success: require same primary over 90 days, with a visit frequency of at least every 13 months.

Formalizing...



Choices for Classifiers

In high dimensions, standard predictors (logistic regression, random forests, neural nets…) often have a tension between sparsity and interpretability.

- “Hip fracture” could code for “elderly”
- “Pregnant” could code for “female”

Thus, we choose to apply topic models for dimensionality reduction, and then predict based on the doc-topic probabilities.

Topic Models

Topics are distributions over words (codes)

$$\phi_k \sim Dir(\alpha_v)$$

Patients are distributions over topics

$$\pi_d \sim Dir(\alpha_p)$$

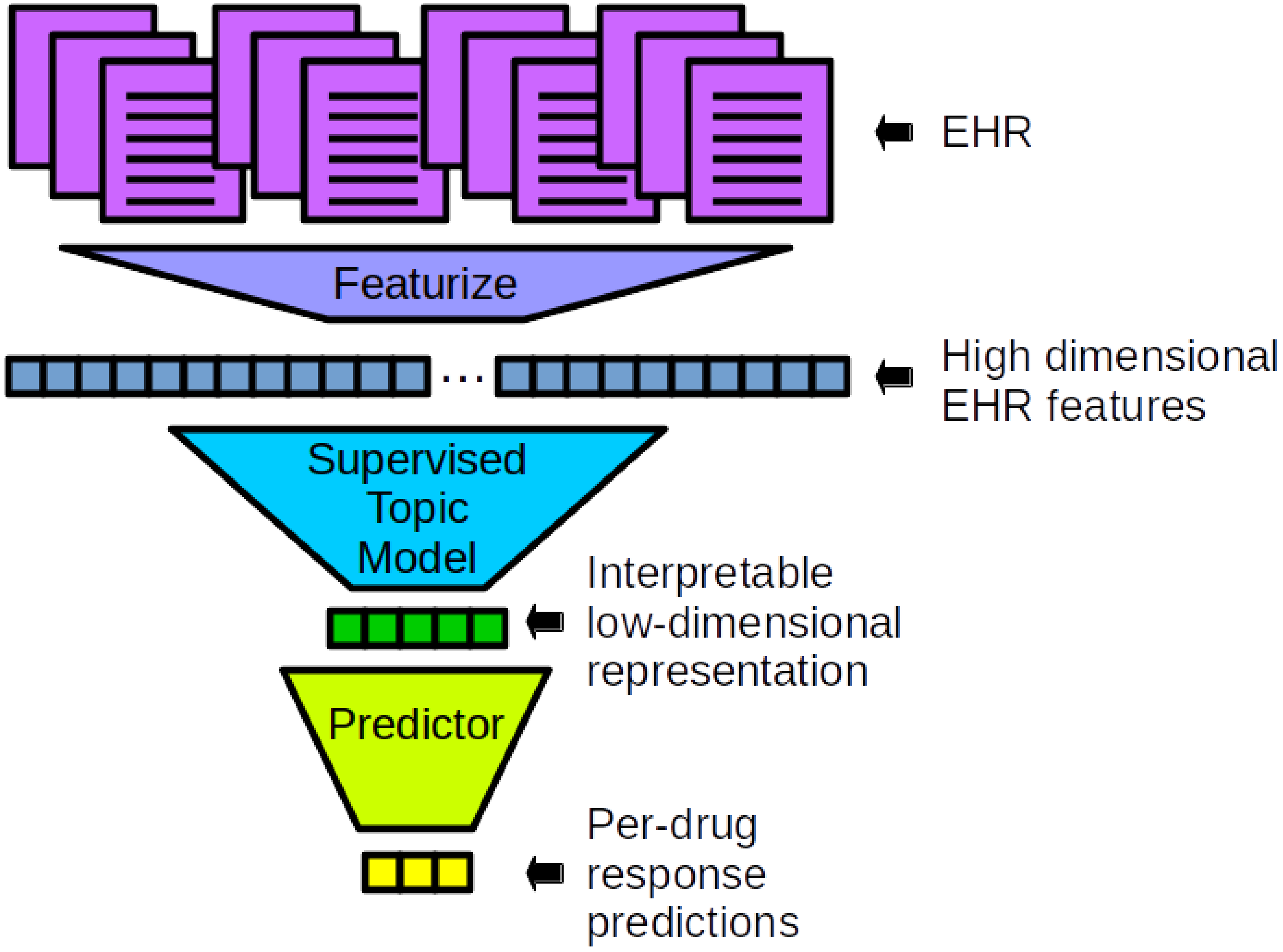
$$w_d^i \sim Dir(\pi_d \phi)$$

Example topic

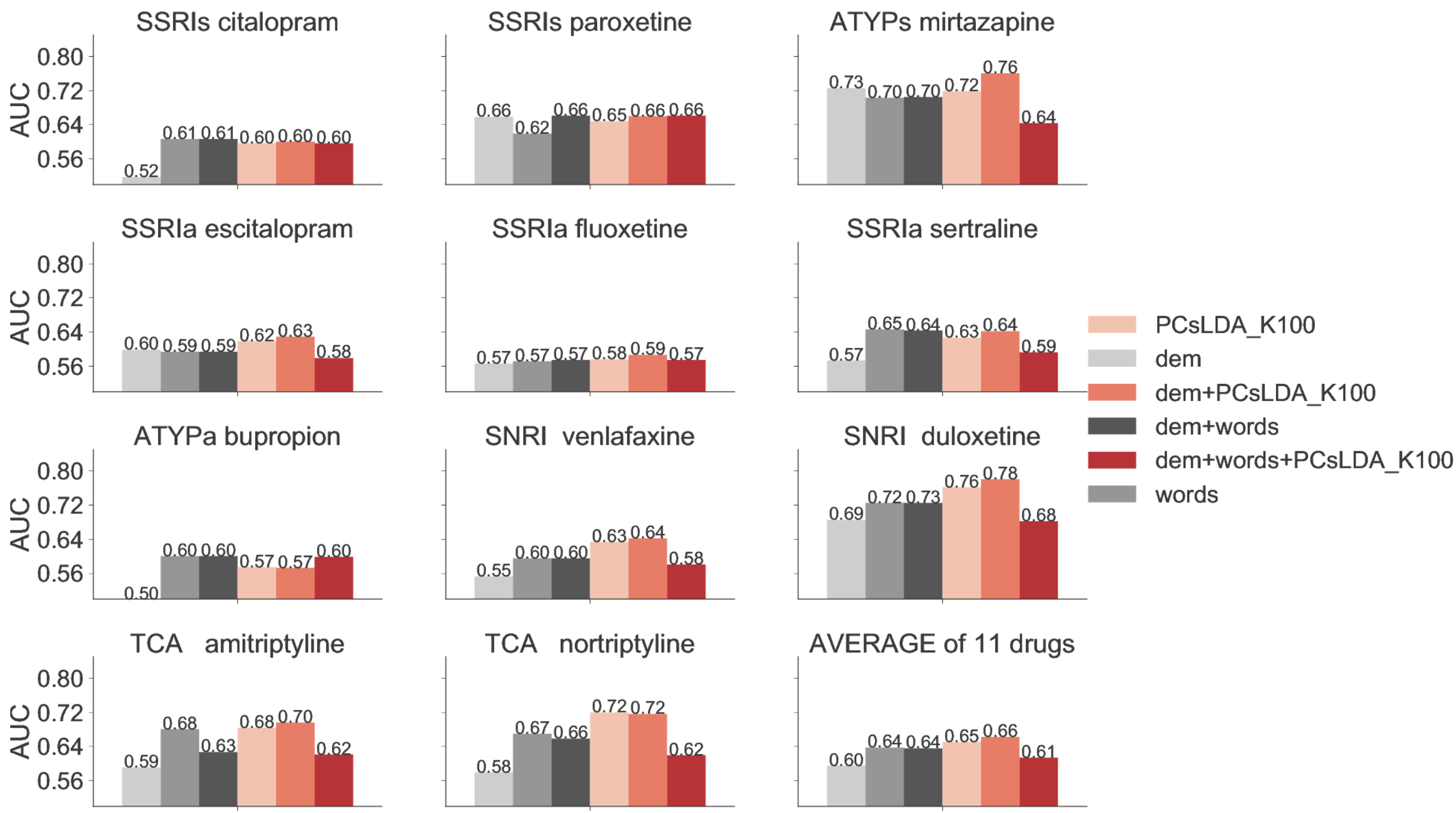
```
1.0000   29650:bipolar_affective_disorder,_depres
0.9999    2967:bipolar_affective_disorder,_unspec
0.9999   29570:schizo-affective_type_schizophreni
0.9999   29660:bipolar_affective_disorder,_mixed,
0.9998  c90870:electroconvulsive_therapy_(include
0.9998  c00104:anesthesia_for_electroconvulsive_t
0.9997   29560:residual_schizophrenia,_unspecifie
0.9996   p9427:other_electroshock_therapy
0.9993  d00061:lithium
0.9993   29653:bipolar_affective_disorder,_depres
0.9985   29651:bipolar_affective_disorder,_depres
0.9985  d04825:aripiprazole
```

Patient has bipolar disorder

Pipeline


EHR
Featurize
High dimensional EHR features
Supervised Topic Model
Interpretable low-dimensional representation
Predictor
Per-drug response predictions

Drug-by-Drug Performance



Interpretation: Bupropion

BPsLDA +7.7
0.60 nortriptyline
0.27 nonspecific abnormal findings
0.21 other specified local infection
0.20 embrionic cyst of the fallopian tube
0.18 application of the intervertebrea...
0.16 other malignant neoplasm...
0.15 amoxicilllin/clarithromycin
0.15 need for prophylactic vaccine
0.15 observation or inpatient visit...

Gibbs -0.6
1.0000 bipolar, depressive
0.9999 bipolar, unspecified
0.9999 schizo-affective schizophrenia
0.9999 bipolar, mixed
0.9998 electroconvulsive therapy
0.9998 anesthesia for ECT
0.9997 residual schizophrenia
0.9996 other electroshock therapy
0.9993 lithium

PCLDA +3.8
0.99 migraine, unspecified, without...
0.99 other malaise and fatigue
0.99 common migraine...
0.99 sumatriptan
0.99 asa/butalbital/caffeine
0.99 zolmitriptan
0.99 migraine, unspecified, with..,
0.99 classical migraine, without...
0.99 classical migraine, with...

Interpretation: Bupropiom

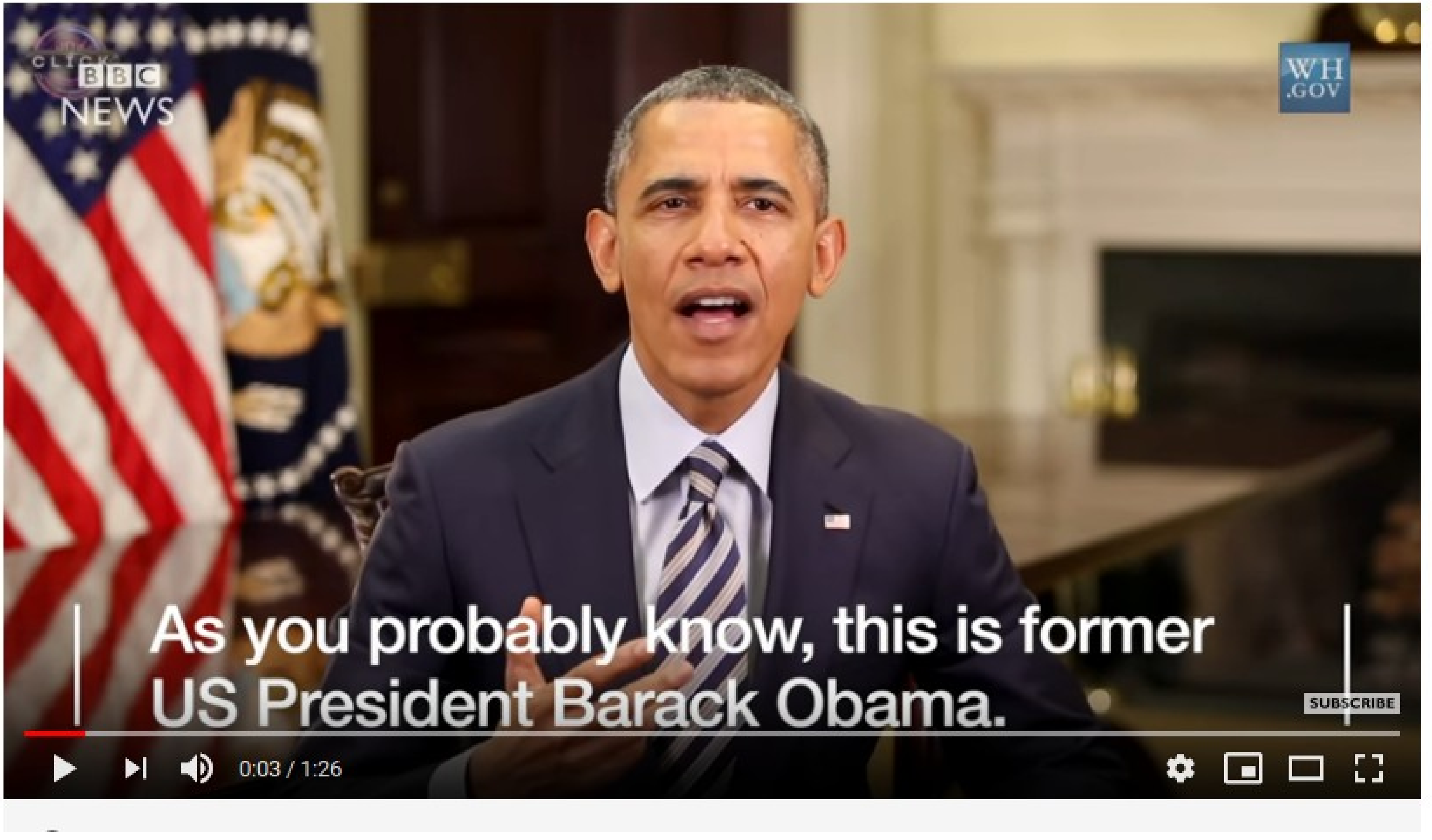
BPsLDA -15.8
0.39 visual field defect, unspecified
0.39 citalopram
0.36 microdissection
0.35 need for prophylactic vaccine
0.31 pet imaging regional or wide area
0.29 visual discomfort
0.29 accident poison by heroin
0.29 personal history of alcohol
0.27 other specified intestinal disorder

Gibbs -2.7
0.9997 respiratory_failure
0.9995 cystic fibrosis...
0.9964 continuous mech ventilation
0.9963 intubation endotracheal

PCLDA -26.4
1.00 semen analysis, complete...
1.00 male infertility, unspecified
1.00 lipoprotein, direct measurement
0.99 sperm isolation, simple…
0.99 tissue culture for non-neoplasm…
0.99 conditions due to anomaly…
0.99 vasectomy, unilateral or…
0.99 arthrocentesis
0.99 scrotal varices

Currently working on how to present these results in a helpful way to practicing clinicians

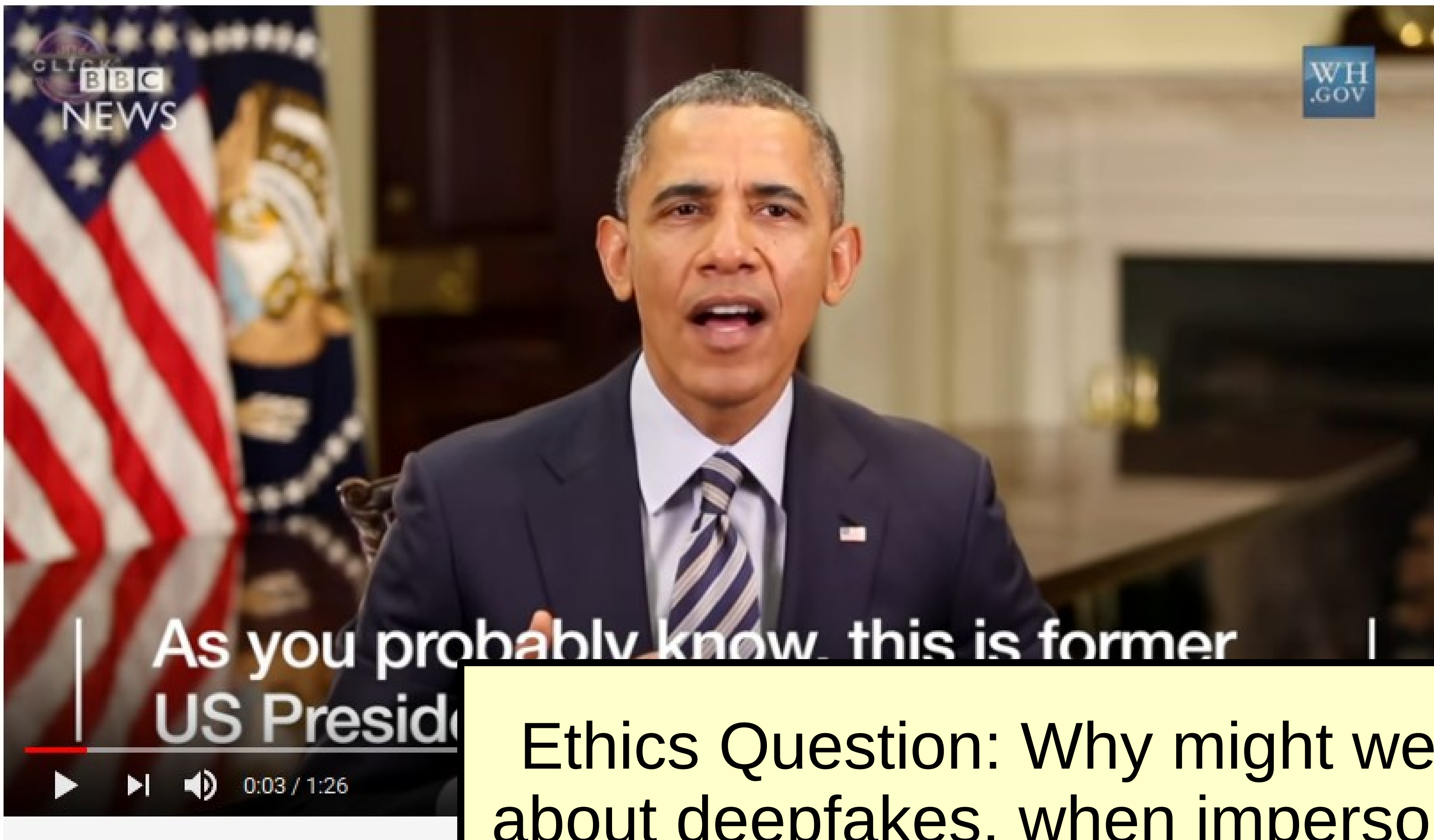
Your Turn: Detecting Fake Videos



Obama: https://www.youtube.com/watch?v=AmUC4m6w1wo&feature=youtu.be

Nixon: https://www.youtube.com/watch?time_continue=2&v=yaq4sWFvnAY&feature=emb_logo

Your Turn: Detecting Fake Videos



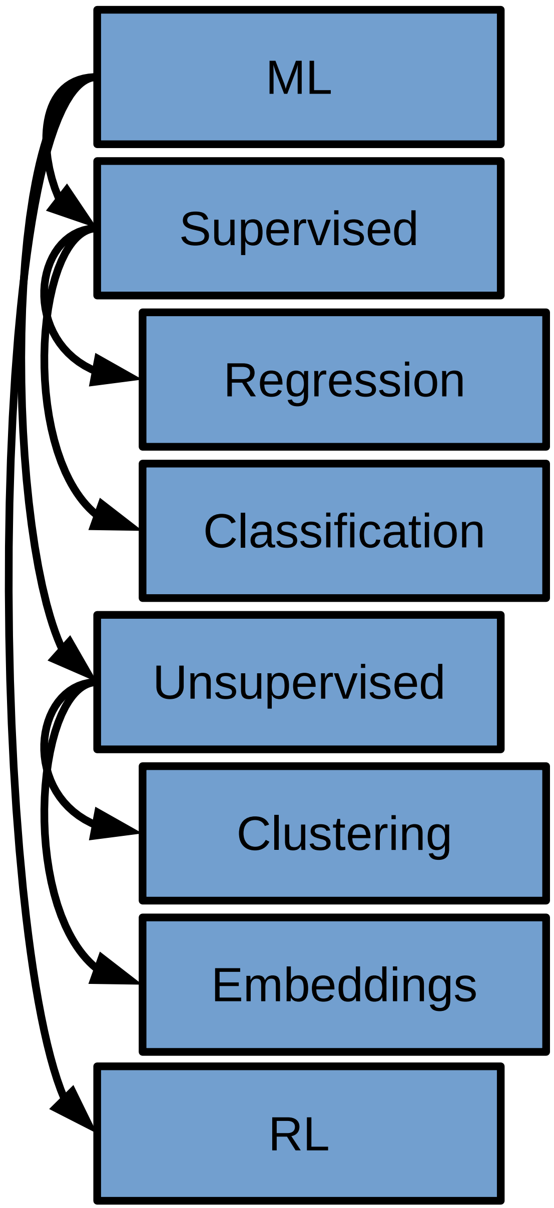
Ethics Question: Why might we care about deepfakes, when impersonation is nothing new? (Think SNL...)

Obama: https://www.youtube.co

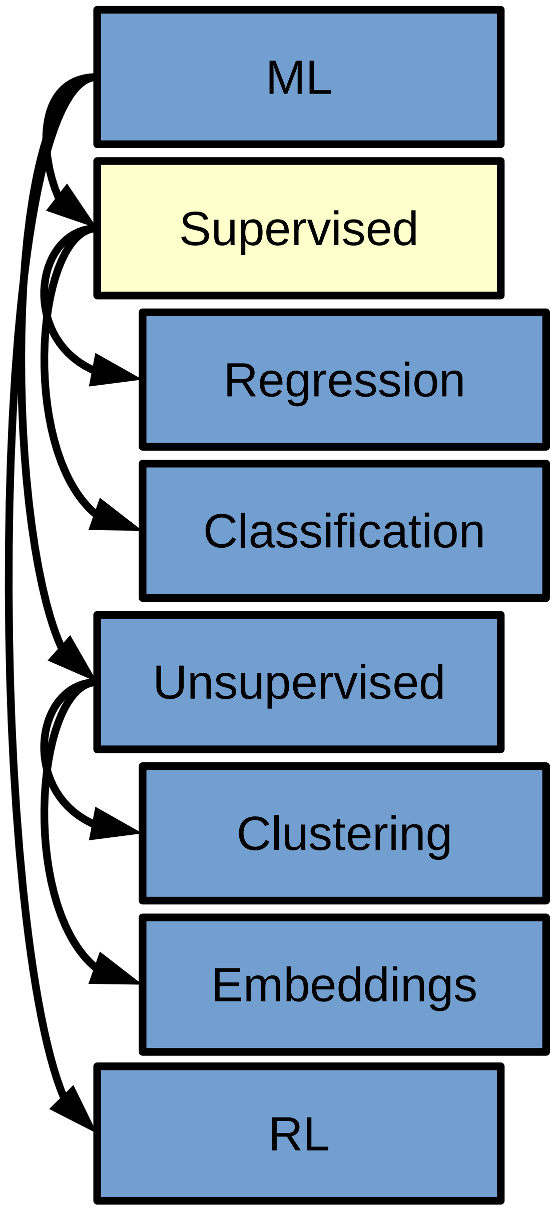
Nixon: https://www.youtube.com/watch?time_continue=2&v=yaq4sWFvnAY&feature=emb_logo

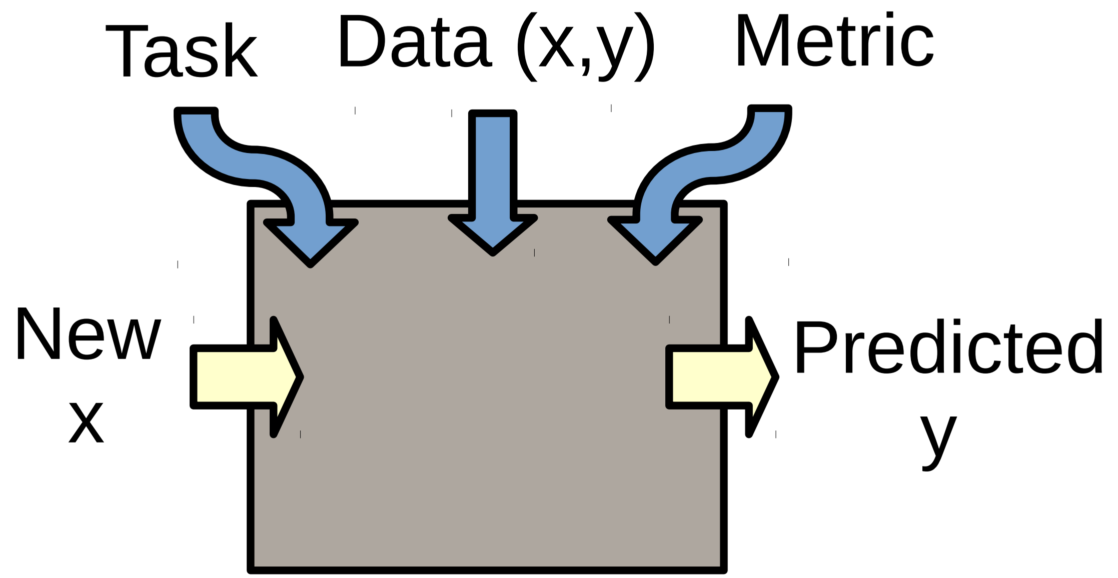
Taxonomy of Problems

Machine Learning Taxonomy

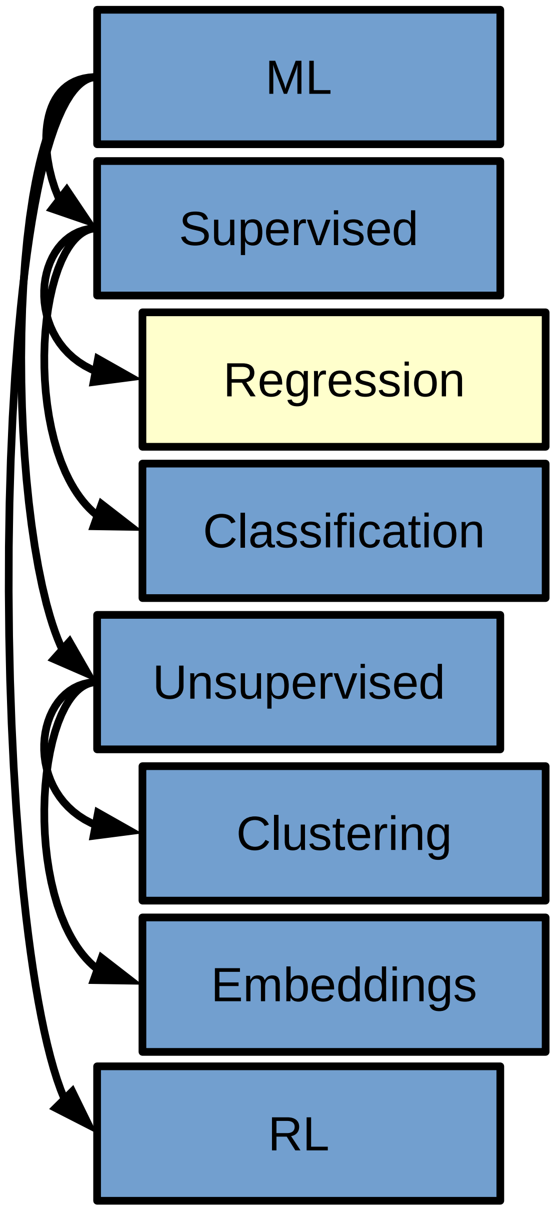


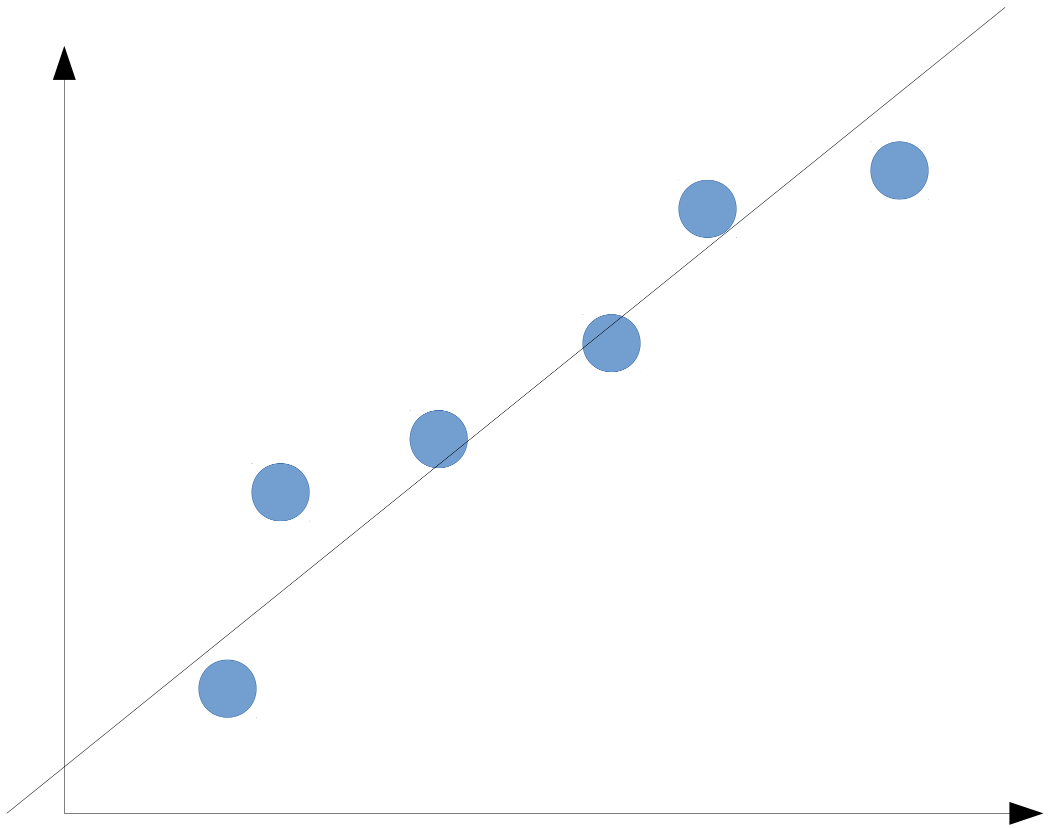
Machine Learning Taxonomy





Terminology: Regression



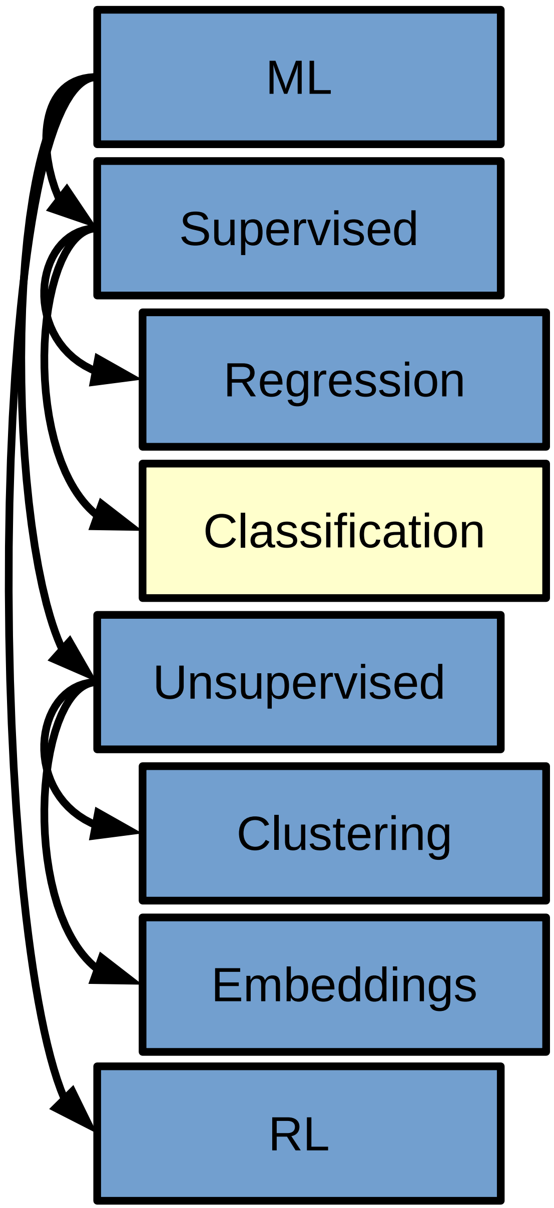


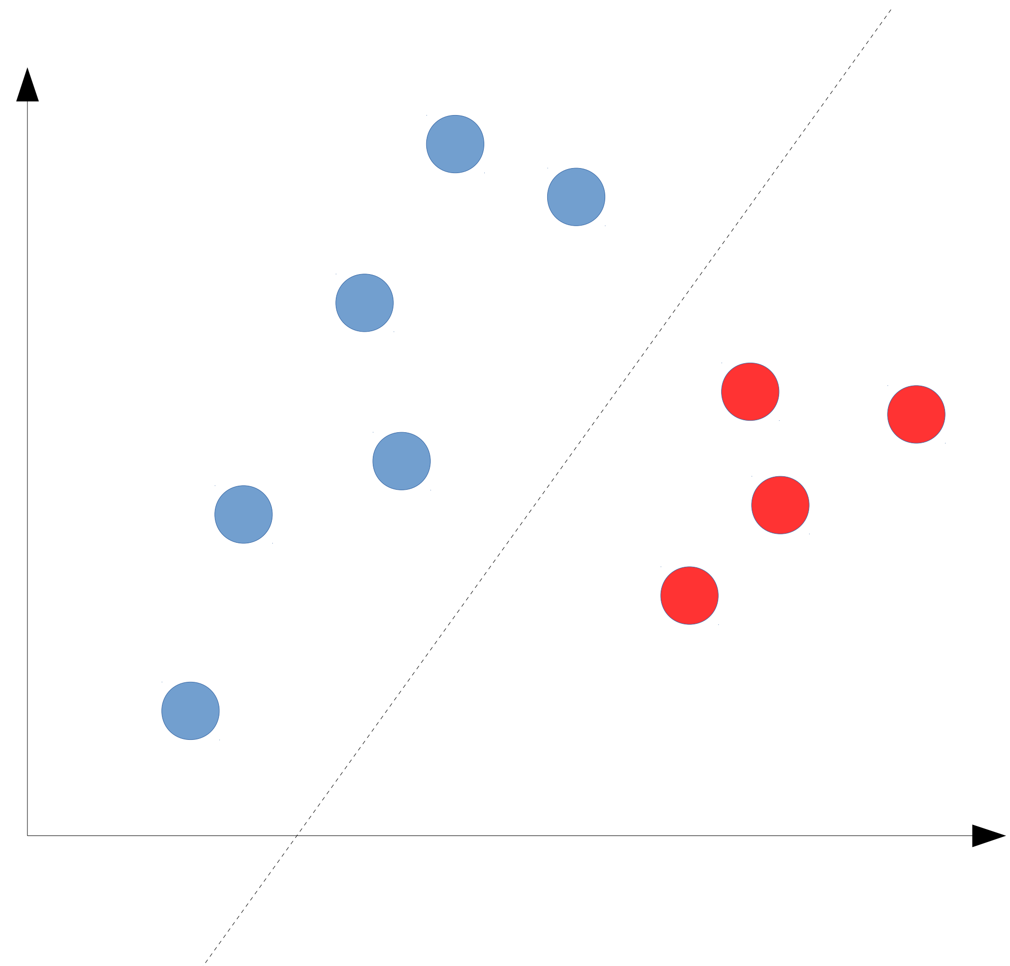
Example: Virtu

VIRTU FINANCIAL

Core technology: Choosing what to trade, and when

Terminology: Classification





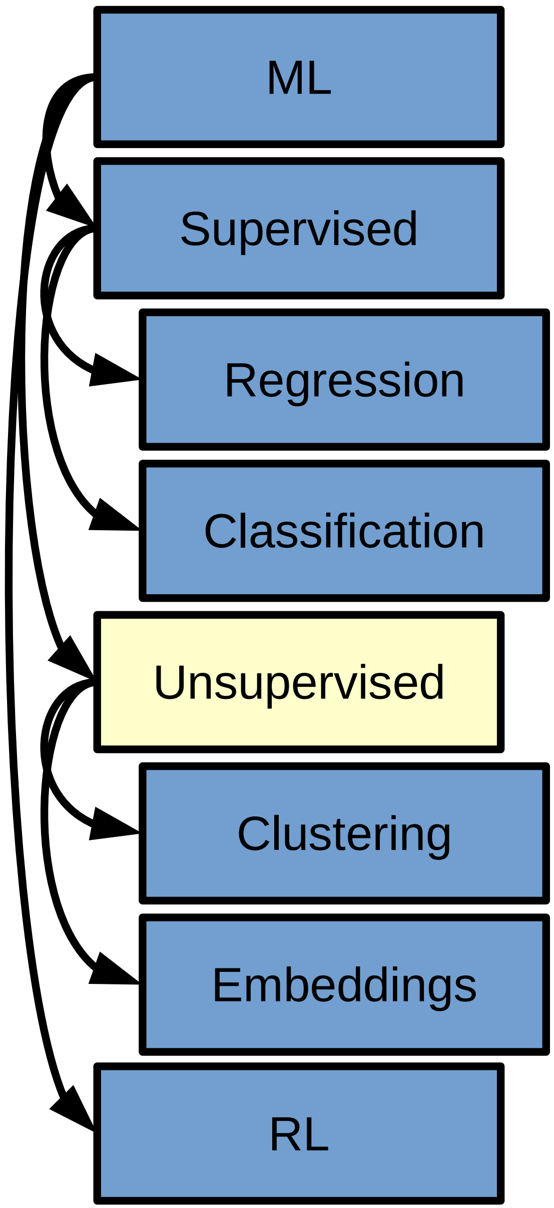
Example: Swype

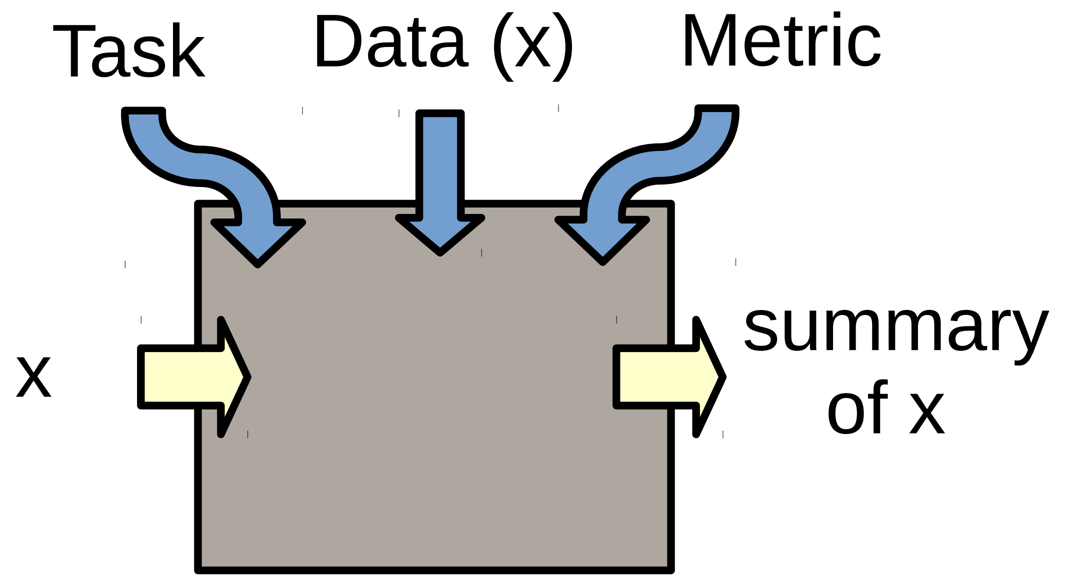
swype

Why type when you can Swype?

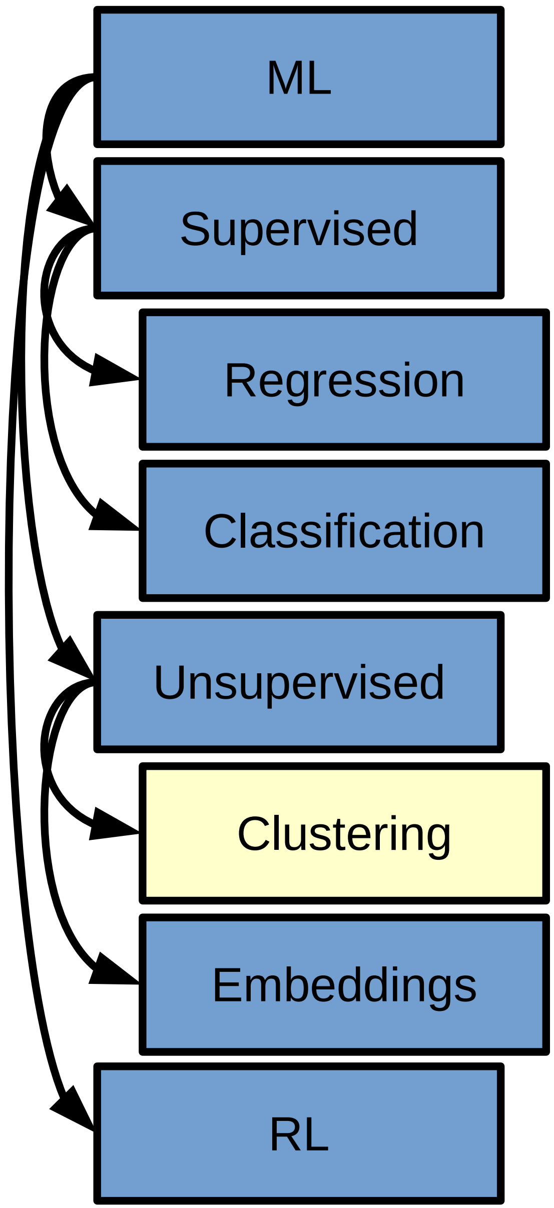
Novel Product: An easier way to input text on mobile devices

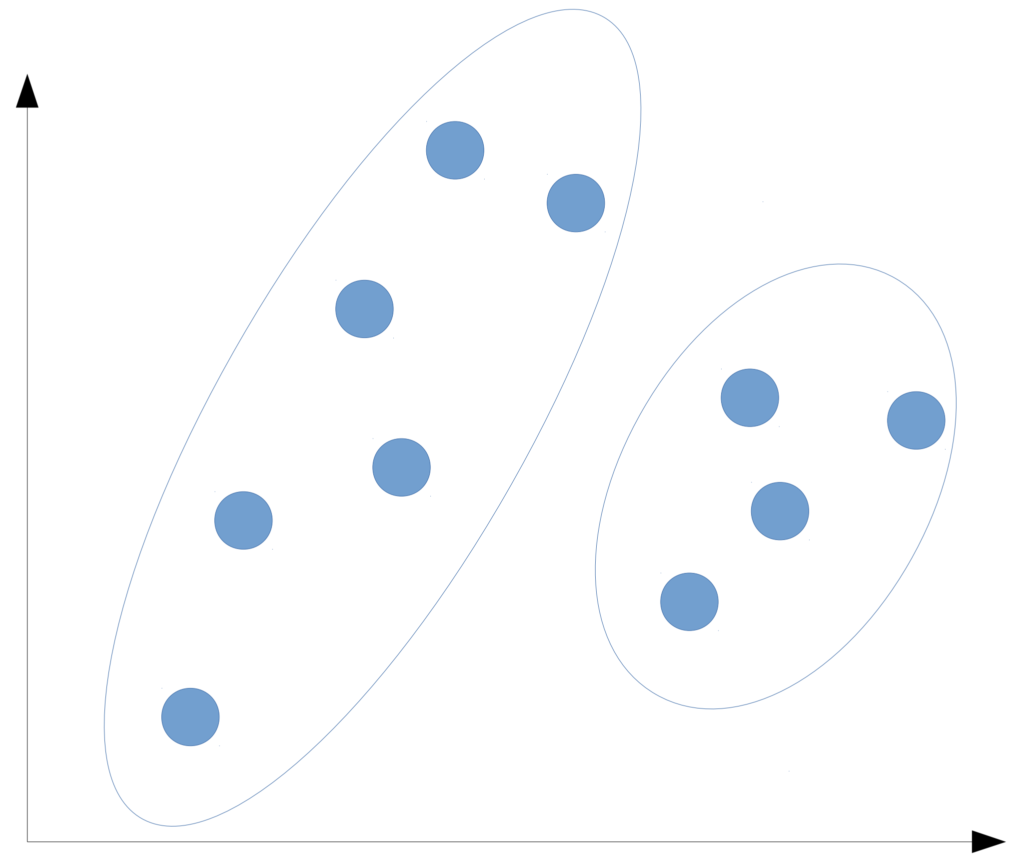
Machine Learning Taxonomy



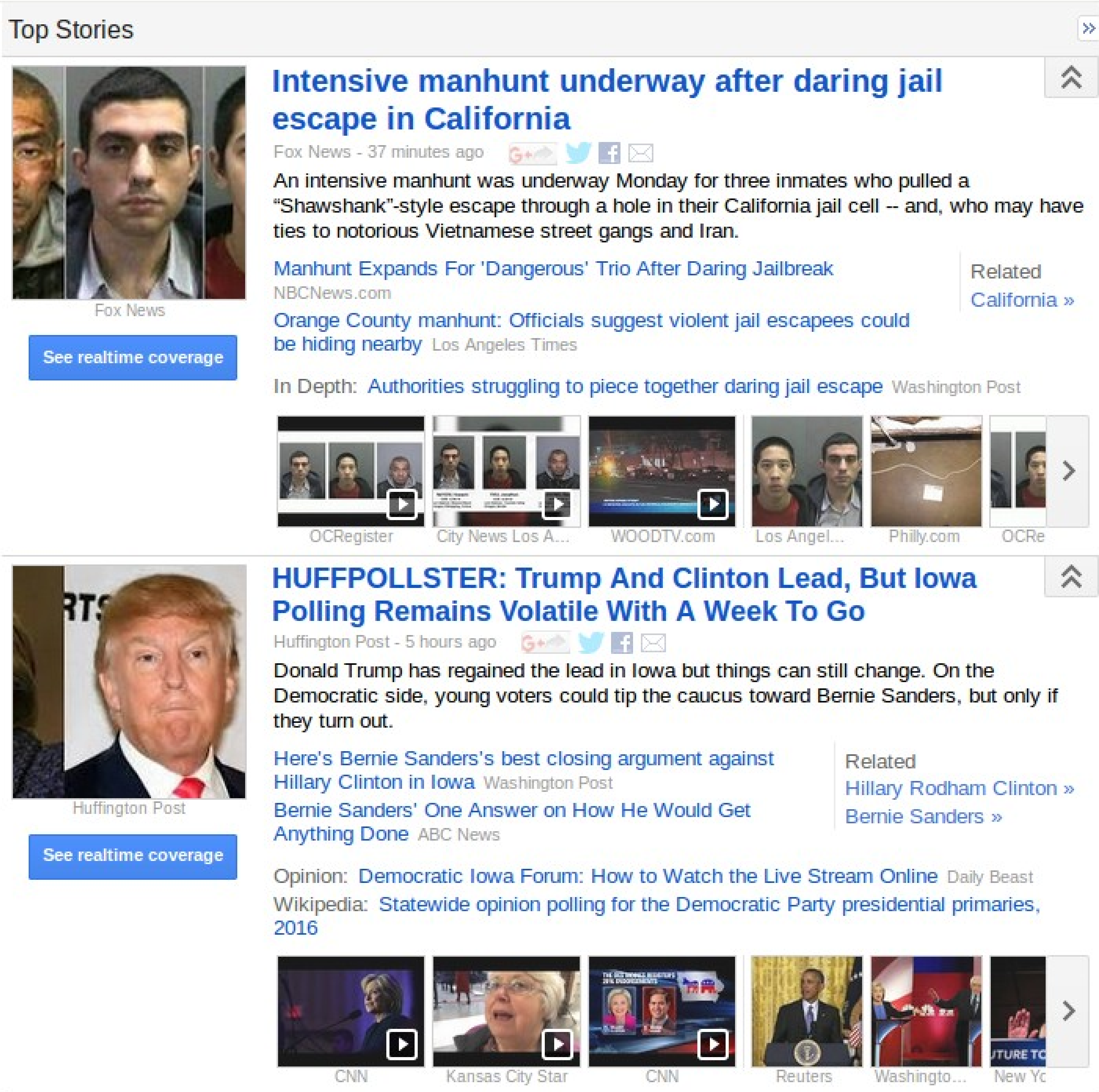


Terminology: Clustering





Example: News



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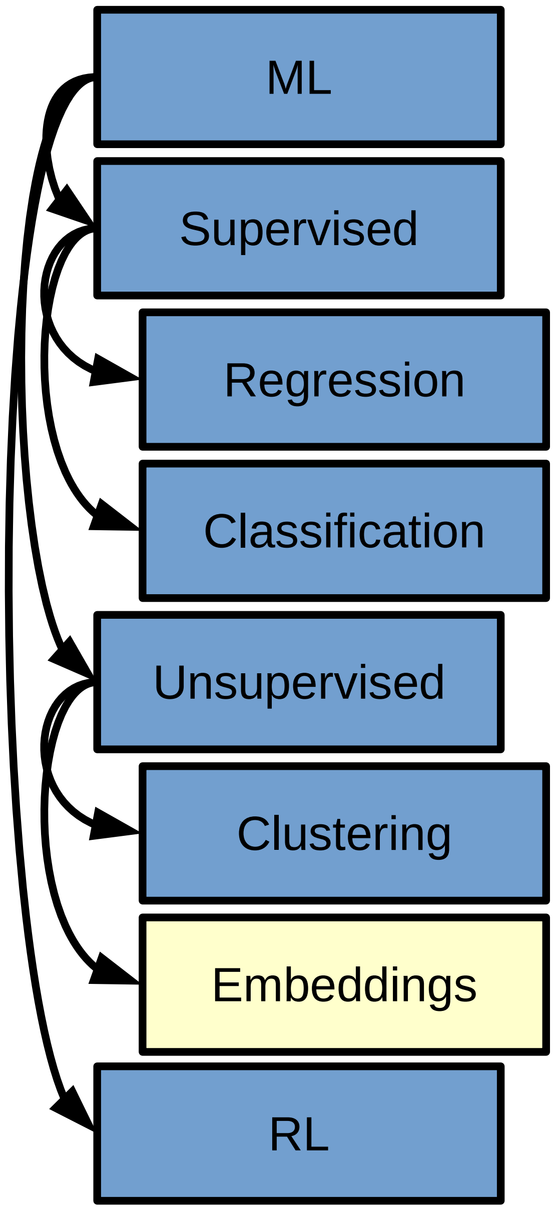
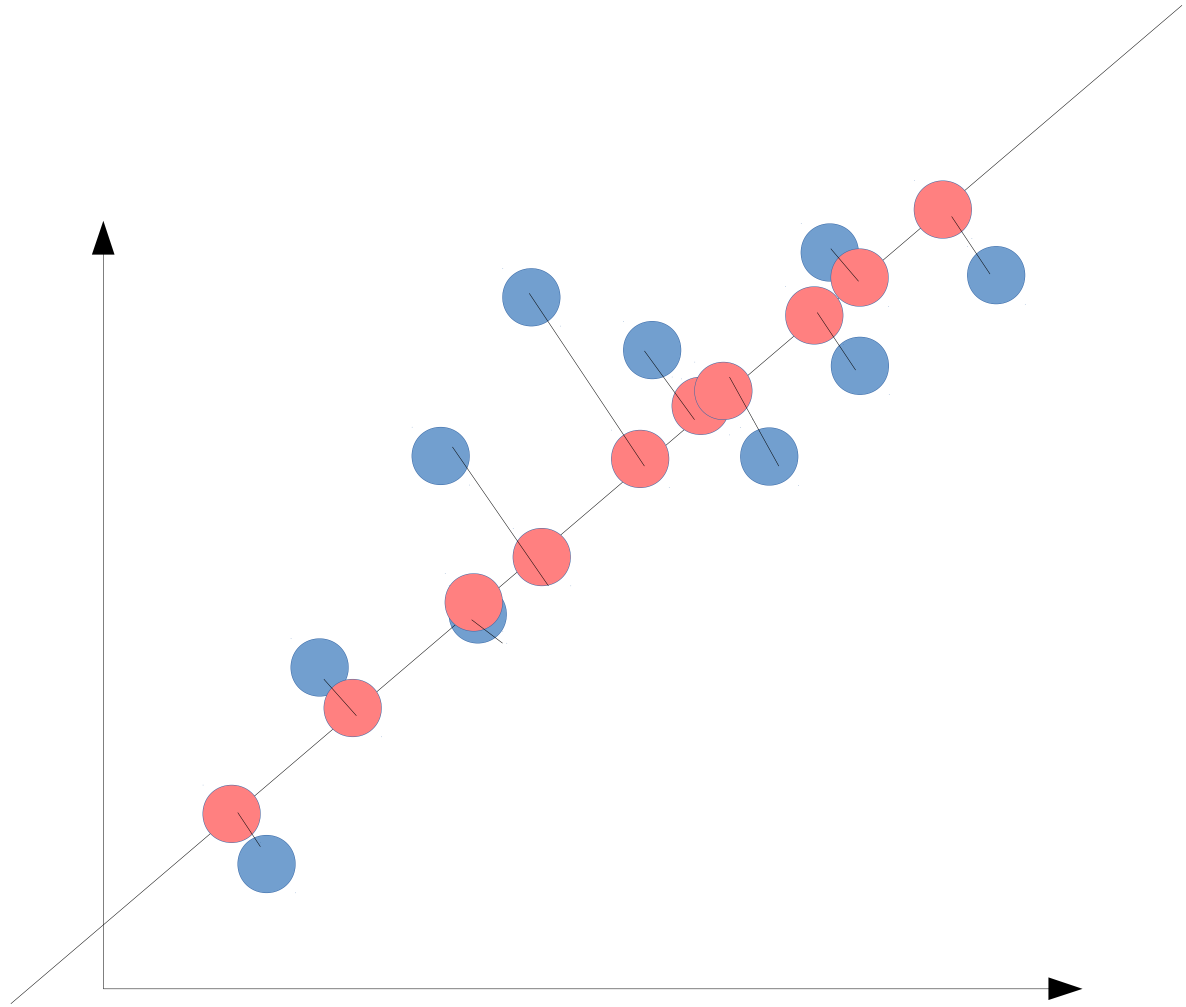
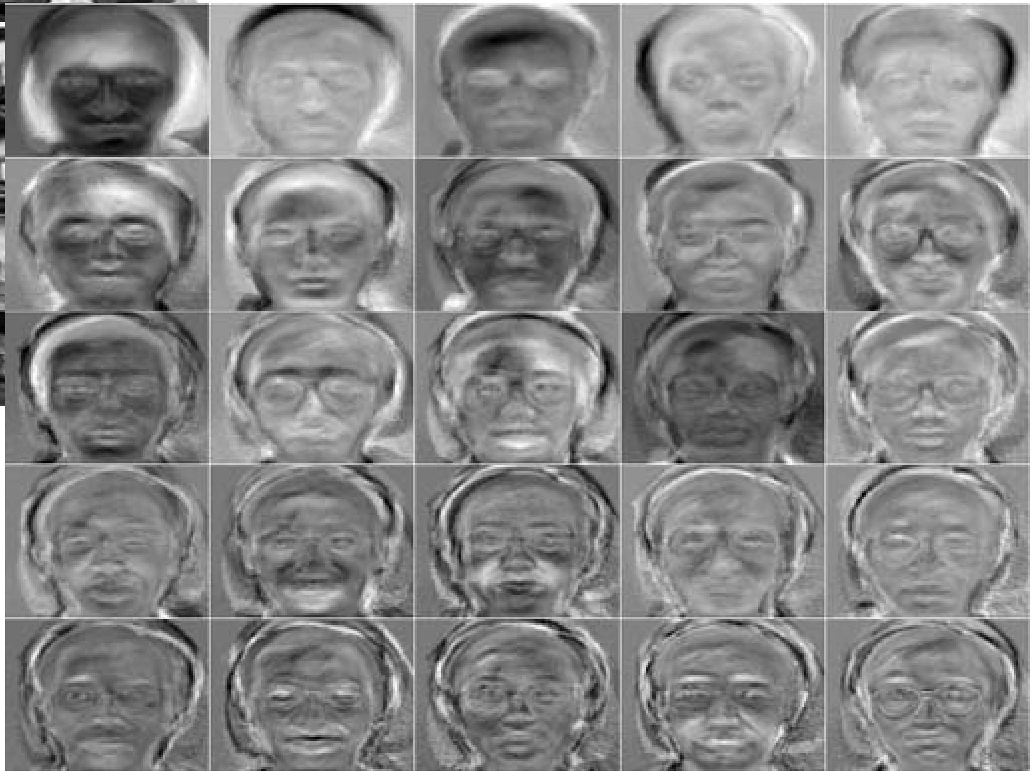
Terminology: Embedding



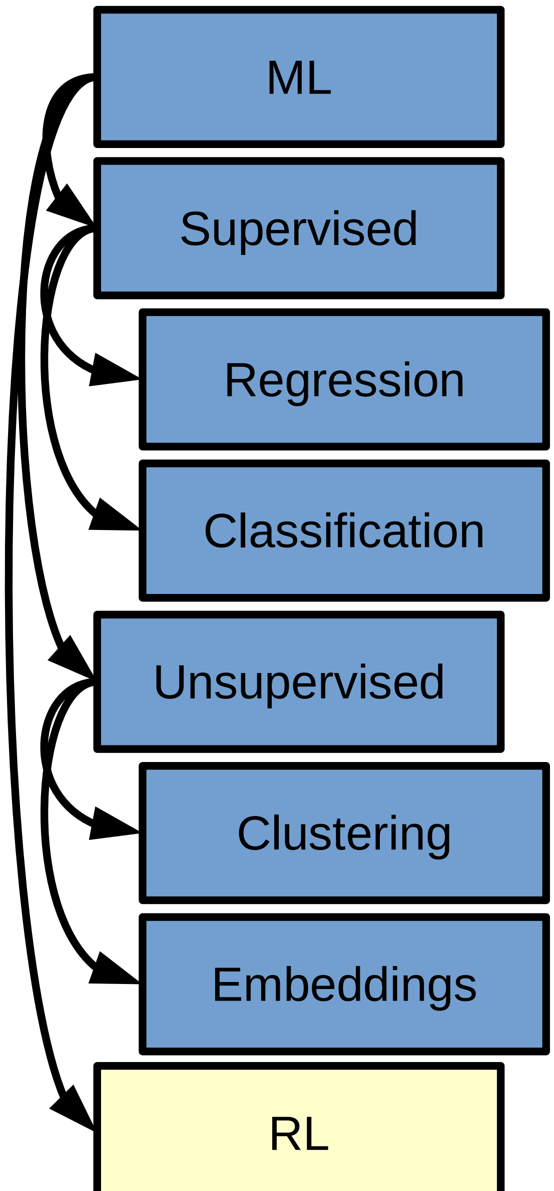


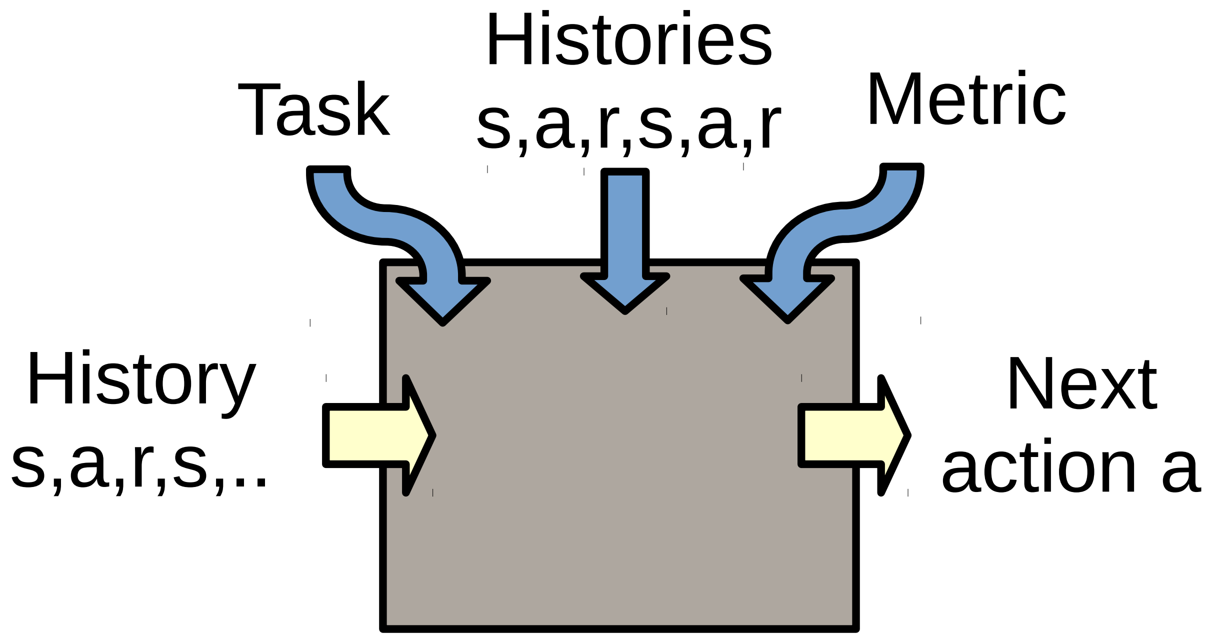
Example: Eigenfaces



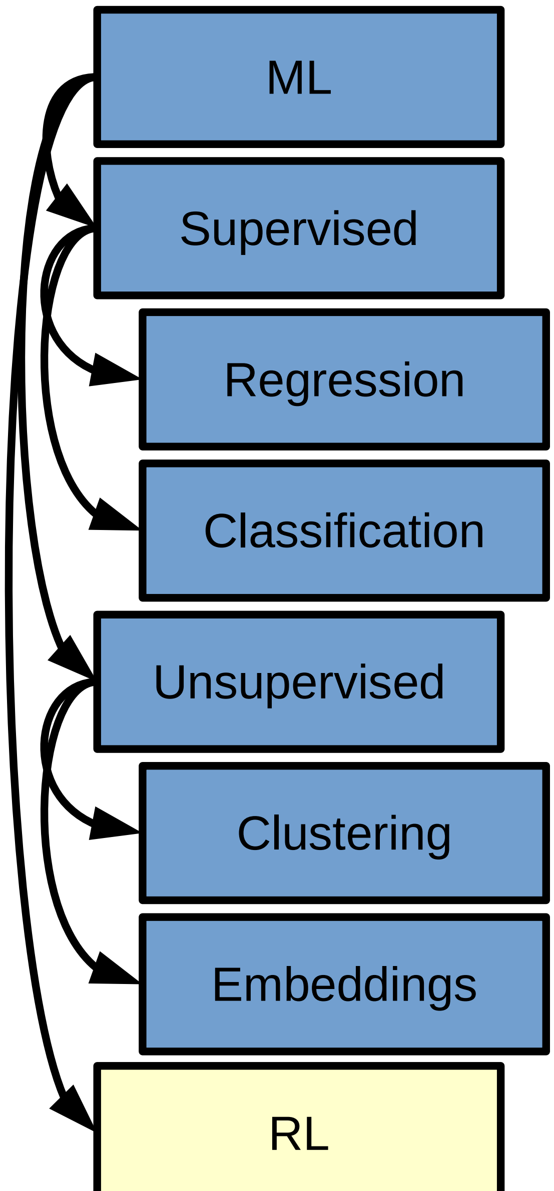
https://www.cs.princeton.edu/~cdecoro/eigenfaces/

Terminology: Reinforcement Learning

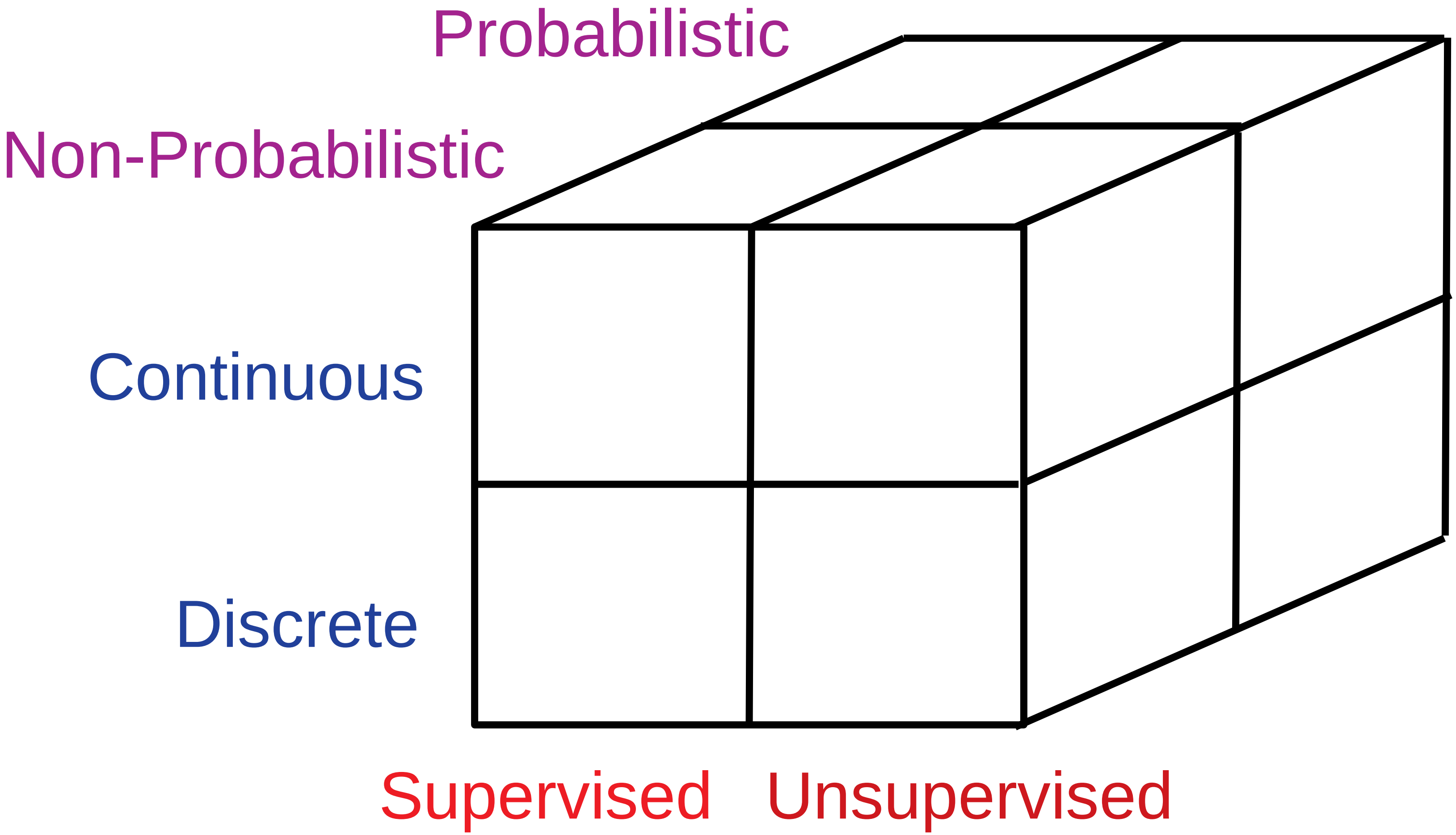




Terminology: Reinforcement Learning



Peter Kormushev, Imperial College



+ Graphical models, reinforcement learning
(some overlap with CS182)

Course Structure

Structure of the Course

- Follow the “cube”++
  - Supervised: regression, classification
  - Unsupervised: classification, embeddings
  - Graphical Models, Reinforcement Learning
- With some excursions to discuss model classes, model selection, evaluation...

Lectures will include real world stories and concept exercises; we’ll also have an embedded ethics component

Logistics

- Notes at https://github.com/harvard-ml-courses/cs181-textbook
- Homeworks: smaller exercises, toy problems (MUST be in LaTeX)
- Sections: math + code review 4:30-5:30 Wednesday, then flipped classroom
- Piazza: Clarification and Content Tags
- GradeScope: Assignments
- Staff organization: Instructor (content), Head TF, TFs

Details on the website

https://harvard-ml-courses.github.io/cs181-web

Read the syllabus!

FAQ: Is this the right course?

- CS181: Rigorous conceptual grounding of a broad range of machine learning ideas with math and code.
- Goal: Reason about when algorithms work and why.
- Alternatives:
  - For mostly theory: Stat195, etc.
  - For mostly practice: CS109, etc.
  - For depth rather than breadth: CS282, etc.
- Check the syllabus/website

FAQ: Can I sit in/audit/take CS181?

Yes!

FAQ: Can I simultaneously enroll?

Maybe: “I will not take advantage of any 1-1 compensatory instruction. I further understand that I, and only I, am solely responsible for anything from lecture, including announcements that are may not be posted anywhere else.”

FAQ: Do I need the Prereqs?

- What you need: programming, statistics, calculus, and linear algebra
- See syllabus references of Math for ML book https://mml-book.com/

Problem 1.1:
Take the gradient with respect to the vector of weights *w*
...

Let’s get technical! Nonparametric Regression