Some Advice on Applying Machine Learning in Practice

CS 760@UW-Madison

It’s generalization that counts

- the fundamental goal of machine learning is to generalize beyond the instances in the training set
- you should rigorously measure generalization
- use a completely held-aside test set
- or use cross validation

It’s generalization that counts

- but be careful not to let any information from test sets leak into training

- be careful about overfitting a data set, even when using cross validation

It’s generalization that counts

- compare multiple learning approaches

- there is no single best approach

Data alone is not enough

- learning algorithms require inductive biases
  - smoothness
  - similar instances having similar classes
  - limited dependencies
  - limited complexity

Media Criticized For Biased Hometown Sports Reporting

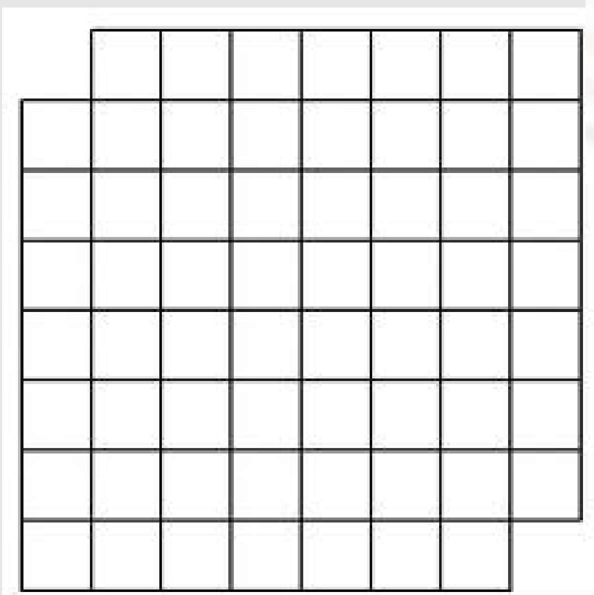
the ONION®
America's Finest News Source

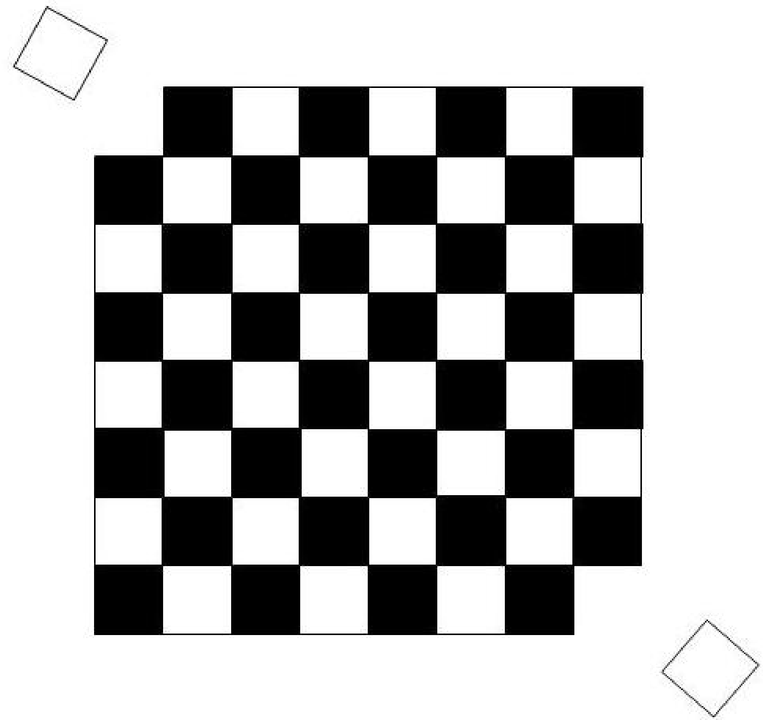
Data alone is not enough

- when choosing a representation, consider what kinds of background knowledge are easily expressed in it
  - what makes instances similar → kernels
  - dependencies → graphical models
  - logical rules → inductive logic programming
  - etc.

The importance of representation

- each domino covers two squares
- can you cover the board with dominoes?





- the solution is more apparent when we change the representation

Feature engineering is key

- typically the most important factor in a learning task is the feature representation
- many independent features that correlate with class → learning is easy
- class is a complex function of features → learning is hard
- try to craft features that make apparent what might be most important for the task

Learn many models, not just one

- winning team and runner-up were both formed by merging multiple teams
- winning systems were ensembles with > 100 models
- combination of the the two winning systems was even more accurate

Learn many models, not just one

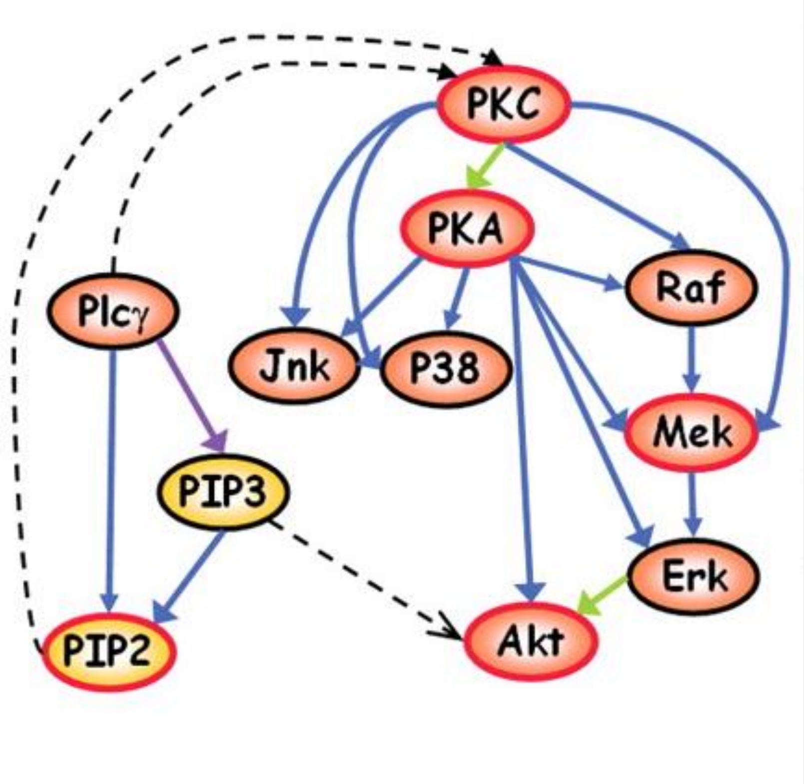
- the lesson is more general than the Netflix prize
- ensembles very often improve the accuracy of individual models

We may care more about the model than actually making predictions

- two principal reasons for using machine learning
  1. to make predictions about test instances
  2. to gain insight into the problem domain
- for the former, a complicated black box may be okay
- for the latter, we want our models to be comprehensible to some degree

We may care more about the model than actually making predictions

- example: inferring Bayesian networks to represent intracellular networks [Sachs et al., *Science* 2005]



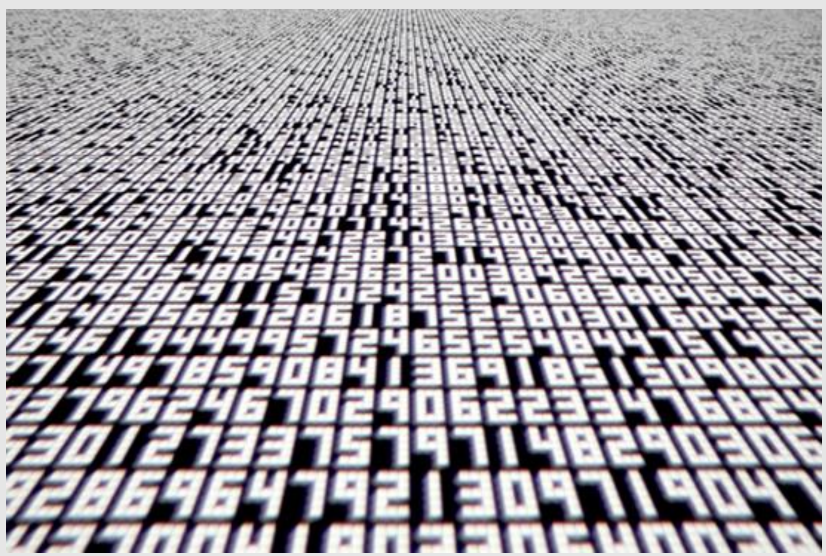
In many cases, we care about both

- example: predicting post-hospitalization VTE risk given patient histories [Kawaler et al., *AMIA* 2012]
  - want to identify patients at risk with high accuracy
  - want to identify previously unrecognized risk factors

Category	Risk Factor
Low Blood Volume	Furosemide
	Hypovolemia
	Hypo-osmolarity
	Posthemorrhagic Anemia
	Acute Renal Failure
Infection	E.Coli Infection
	Levofloxacin
	Cephalexin
Inflammation	High Alpha-1 Globulin Count
	Angina Pectoris
Immobilization	Pathologic Fracture of Vertebrae
Malnutrition	Protein Caloric Malnutrition

Theoretical guarantees are not what they seem

- PAC bounds are extremely loose
- asymptotic results tell us what happens when given infinite amounts of data – we don't usually have this
- learning theory results are generally
  - useful for understanding learning, driving algorithm design
  - not a criterion for practical decisions



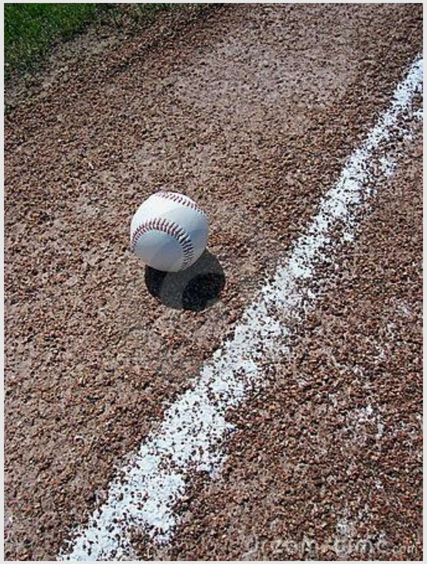
Do assumptions of algorithm hold?

- be sure to check the assumptions made by an approach/methodology against your problem domain
  - Are the instances *i.i.d.* or should we take into account dependencies among them?
  - When we divide a data set into training/test sets, is the division representative of how the learner will be used in practice?
  - etc.

- questioning the assumptions of standard approaches sometimes results in new paradigms
  - active learning
  - multiple-instance learning
  - etc.

Compare against reasonable baselines

- Empirically determine whether fancy ML methods have value by comparing against
  - simple predictors (e.g. tomorrow’s weather will be the same as today’s)
  - standard predictors in use
  - individual features



THANK YOU

Some of the slides in these lectures have been adapted/borrowed from materials developed by Mark Craven, David Page, Jude Shavlik, Tom Mitchell, Nina Balcan, Elad Hazan, Tom Dietterich, and Pedro Domingos.