Big Data, Model Complexity, and Interpretability: Machine Learning and Finance

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Statistics/Econometrics "vs." Machine Learning

- Differences in communities, culture, practices
  - BUT: communities are learning a lot from each other and coming closer
  - Ideas come from both sides (e.g. bootstrap came from statistics to ML)
- (Supervised) ML has more of a focus on:
  - (Out-of-sample) prediction (vs. hypothesis testing or causal inference)
  - Algorithmic questions (esp. in high-dimensional problems)
  - Empirical (finite-sample) evaluation vs. asymptotics

Predictive Inference

- Clear use case: Solve a prediction problem and use the predictions for a meaningful task.
- E.g. “Prediction Policy Problems” (Kleinberg et al., 2015) example:
  - $\approx 500,000$ Medicare beneficiaries receive hip or knee replacements every year
  - Costs are both monetary and quality-of-life (first 6 months are particularly tough for recipients, but outcomes improve by 12 months)
  - However, 1.4% of recipients dies in the month after surgery and 4.2% in months 1-12
  - These 4.2% are highly predictable using ML methods. For this population, having the surgery was probably a bad decision in terms of QOL.
  - Don’t need to establish causality in order to improve outcomes in expectation (ethical issues can be a concern).

Goals

- Explain how machine learners view the world.
- Discuss what we're good at, and what the state of the art is, with a focus on things that might be of value to MFM scholars.
- Talk about a couple of examples in a bit of detail.

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- Talk about a couple of examples in a bit of detail.
- ~~Discuss causality~~: Machine learning has a lot to learn
- ~~Talk about using ML to sell ad space on the web~~

Outline

- Basic framework: How (supervised) machine learners think
- State of practice in prediction problems
  - Algorithms: SVMs, ensemble methods, etc.
  - Optimization and design choices
- Prediction problems and applications in finance
- Text analysis and applications

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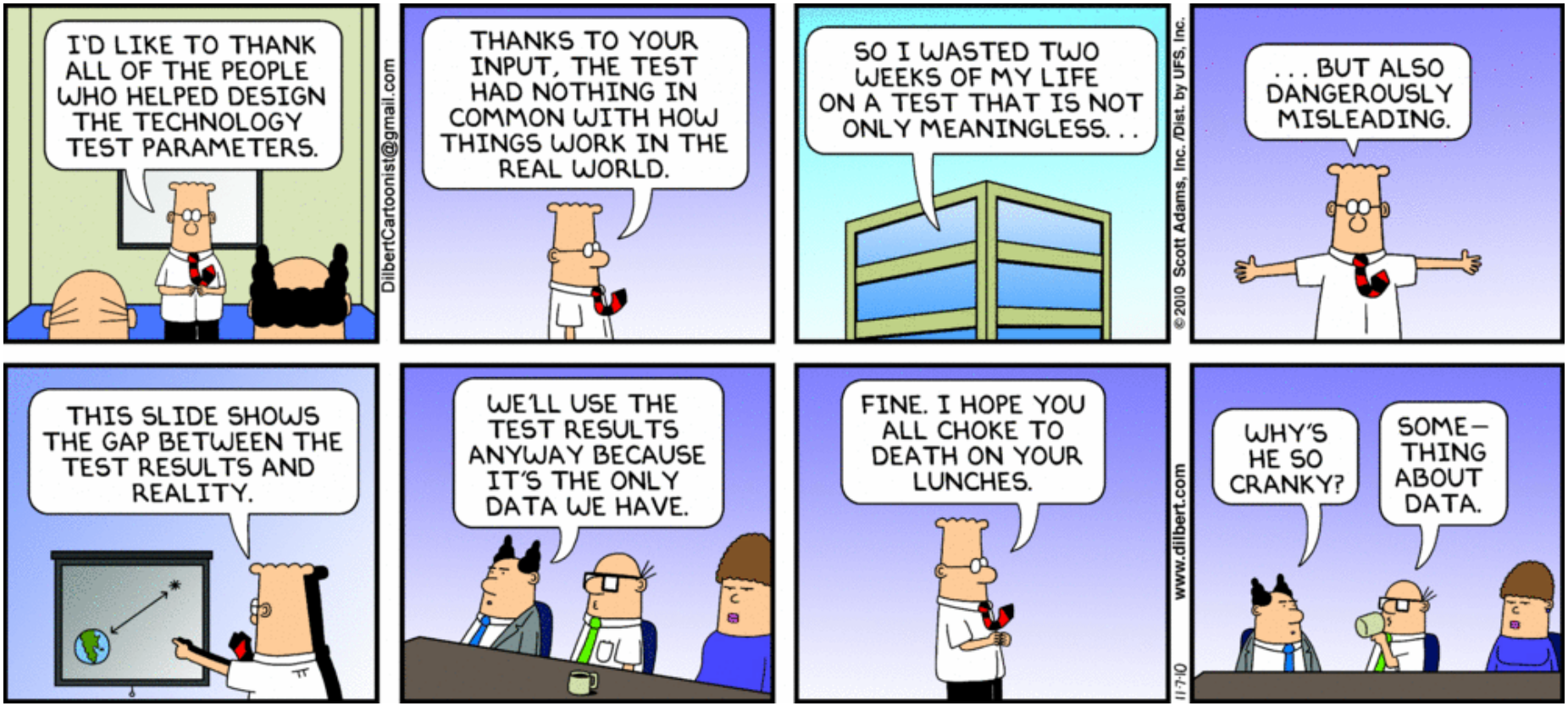
The Supervised Learning Problem

- Unknown target function $f : \mathcal{X} \rightarrow \mathcal{Y}$
- Training data $\mathcal{D} : (\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots (\mathbf{x}_n, y_n)$ where $y_i = f(\mathbf{x}_i)$ (possibly noisy).
- Want to learn h "close to" f.
- Two central questions:
  - How do we learn h?
  - What can we say about how close h is to f?

(Note: My development and notation here follows that of Abu-Mostafa, Magdon-Ismail, and Lin (2012)).

Generalization Error



(©Scott Adams: `http://dilbert.com/strips/comic/2010-11-07/`)

Generalization Error

- Standard for closeness that we care about $E_{\text{out}}(h) = \Pr[h(\mathbf{x}) \neq f(\mathbf{x})]$, where the probability is based on the sampling distribution on $\mathcal{X}$.
- In practice, we estimate E_{out} by evaluating on a (held-out) *test set*.
- There are a ton of interesting problems when the sampling distribution for test data is not the same as that for $\mathcal{D}$.

How Do We Learn f?

- Pick a *hypothesis set* $\mathcal{H} = \{h_1, h_2, \ldots, \}$
- Use a *learning algorithm* to select a hypothesis from $\mathcal{H}$ on the basis of $\mathcal{D}$.
- The choice of $\mathcal{H}$ and the learning algorithm are intertwined

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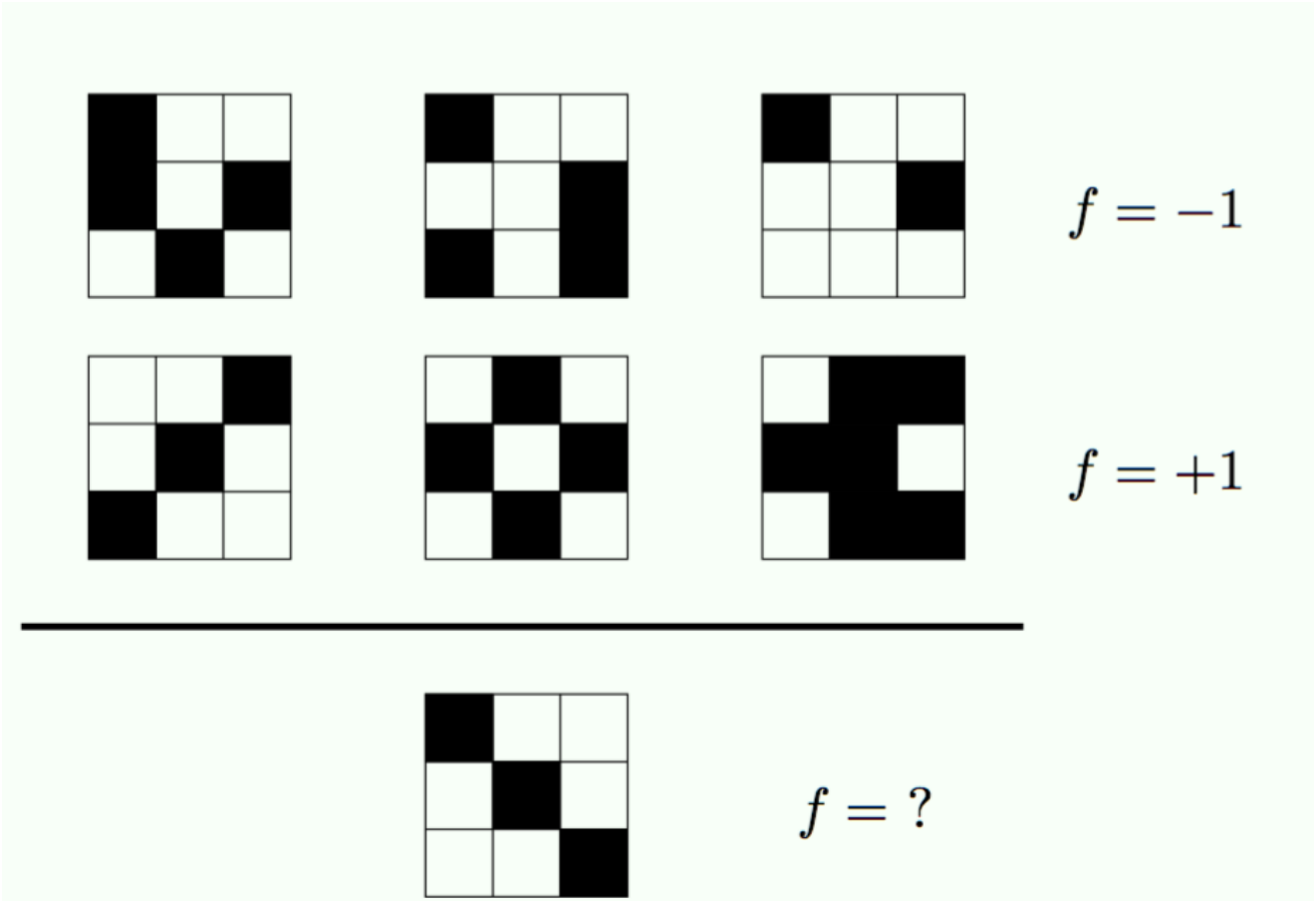
- The choice of $\mathcal{H}$ and the learning algorithm are intertwined
- No free lunch in machine learning

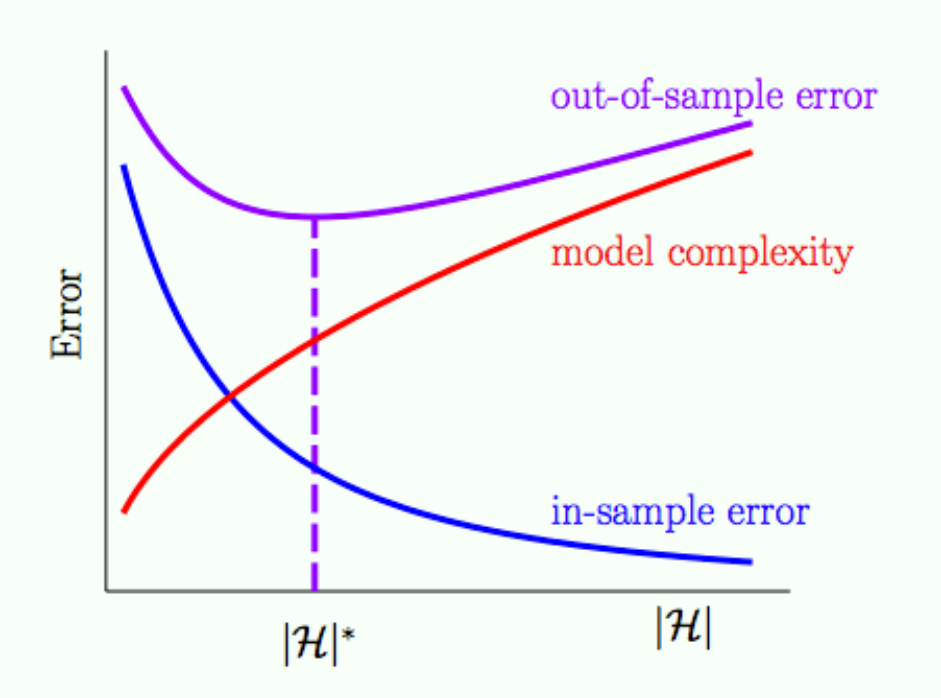


Choosing h from $\mathcal{H}$

- First thought: Minimize $E_{\text{in}}(g) = \frac{1}{n}\sum_{i=1}^{n}[h(\mathbf{x}_i) \neq f(\mathbf{x}_i)]$
- Many algorithms can be thought of within this broad framework.
  - Linear regression: Find a weight vector $\mathbf{w}$ that minimizes $E_{\text{in}}(\mathbf{w}) = \frac{1}{n}\sum_{i=1}^{n}(\mathbf{w}^T\mathbf{x}_i - f(\mathbf{x}_i))^2$
  - Logistic regression: Find a linear function that minimizes $E_{\text{in}}(\mathbf{w}) = \frac{1}{n}\sum_{i=1}^{n}\ln(1 + e^{-y_i\mathbf{w}^T\mathbf{x}_i})$
  - Decision trees: Find the tree that directly minimizes the above. Problem: Computationally intractable, so we use greedy heuristics

Minimizing E_{out}

- But E_{in} is not really our objective. Vapnik-Chervonenkis and PAC theory tell us (roughly) that $E_{\text{out}}(g) \leq E_{\text{in}}(g) + \Omega(\mathcal{H})$ where $\Omega(\mathcal{H})$ penalizes complexity of the hypothesis class. Gives us two objectives:
  - Control hypothesis-class complexity
  - Minimize E_{in}



(from (Abu-Mostafa, Magdon-Ismail, and Lin, 2012))

The Central Problems

- There are deep relationships between the stability and variance of a learning algorithm, hypothesis complexity, and generalization ability.
- Bigger data $\rightarrow$ more complex hypothesis spaces can generalize better.
- Different ML algorithms arise from different choices related to two questions:
  - What $\mathcal{H}$ to search
  - What and how to optimize in the search process

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Linear Models and SVMs

- Regularized logistic regression: Minimize $E_{\text{in}}(\mathbf{w}) = \frac{1}{n}\sum_{i=1}^{n} \ln(1 + e^{-y_i \mathbf{w}^T \mathbf{x}_i}) + \lambda \mathbf{w}^T \mathbf{w}$.
  - Often used with text data.
  - In general performs better than Naive Bayes.

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  - Often used with text data.
  - In general performs better than Naive Bayes.
- Support vector machines: Minimize $E_{\text{in}}(\mathbf{w}) = \frac{1}{n}\sum_{i=1}^{n}(1 - y(\mathbf{w}^T \mathbf{x}_i)_+) + \lambda \mathbf{w}^T \mathbf{w}$ where $(z)_+ \equiv \max(z, 0)$ is the *hinge loss*.
  - Same thing as maximizing the margin. The dual QP has a nice interpretation in terms of "support vectors" (points at or within the margin).
  - When combined with the kernel trick, SVMs give a natural and powerful regularized non-linear classifier.
  - Try quadratic and RBF kernels if needed.

Decision Trees

- Flexible and rich hypothesis space. Easy to express trees in terms of a combination of rules.
- Impossible to find the optimal tree, so we use greedy heuristics to construct the tree.
- High variance classifier
  - Because of the greedy nature, a small change can have huge cascading effect, leading to totally different trees.
- Frequently used as a building block for ensemble methods.

Random Forests

- Construct k decision trees on bootstrapped replicates of the training set.
- Use random feature selection on the nodes (typically $\sqrt{\#\text{ features}}$) to decorrelate trees further.
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- Use random feature selection on the nodes (typically $\sqrt{\#\text{ features}}$) to decorrelate trees further.
- The ensemble votes on any new example.
- Off-the-shelf state of the art performance.
- Out-of-bag error provides a great estimate of out-of-sample error for free.
- Implementations come along with a feature scoring method that gets used a lot (measuring decrease in accuracy when permuting a feature in all OOB samples)

Boosting

- Arose as the answer to a theoretical question: Given a black-box weak learner (slightly better than chance), can we “boost” it into a strong learner.
- Key idea: Each new weak learner is trained on a distribution of examples modified to give more weight to those the existing ensemble has most trouble with.

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- Arose as the answer to a theoretical question: Given a black-box weak learner (slightly better than chance), can we "boost" it into a strong learner.
- Key idea: Each new weak learner is trained on a distribution of examples modified to give more weight to those the existing ensemble has most trouble with.
- A variant called *gradient boosting* is also state-of-the-art.
- Typically use decision stumps or short decision trees as the weak learners.
- If you need a powerful ML algorithm, try random forests andor gradient boosting first..

Deep Learning

- (Massively) multilayer neural networks, typically trained using GPUs with huge training datasets.
- Optimization, structure, and regularization are all arts that are slowly becoming more “off the shelf” but aren’t there yet.
- It appears they learn interesting intermediate representations.
- Have been hugely influential in computer vision and NLP.
- Why they work is still a major theoretical puzzle.

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Model Selection

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- Classic answer: Cross-validation and grid search over the space of parameters
- Taking over: Bayesian Optimization
  - Use a Gaussian Process prior over the value of the function being optimized (say error) and iteratively evaluate at different hyperparameter values (Shahriari et al., 2016; Snoek, Larochelle, and Adams, 2012; Osborne, Garnett, and Roberts, 2009).
  - Spearmint (`https://github.com/HIPS/Spearmint`) is a well-known package for BO.

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Some Trends in Current Research

- Can predictive analytics provide business or regulatory value and insight?
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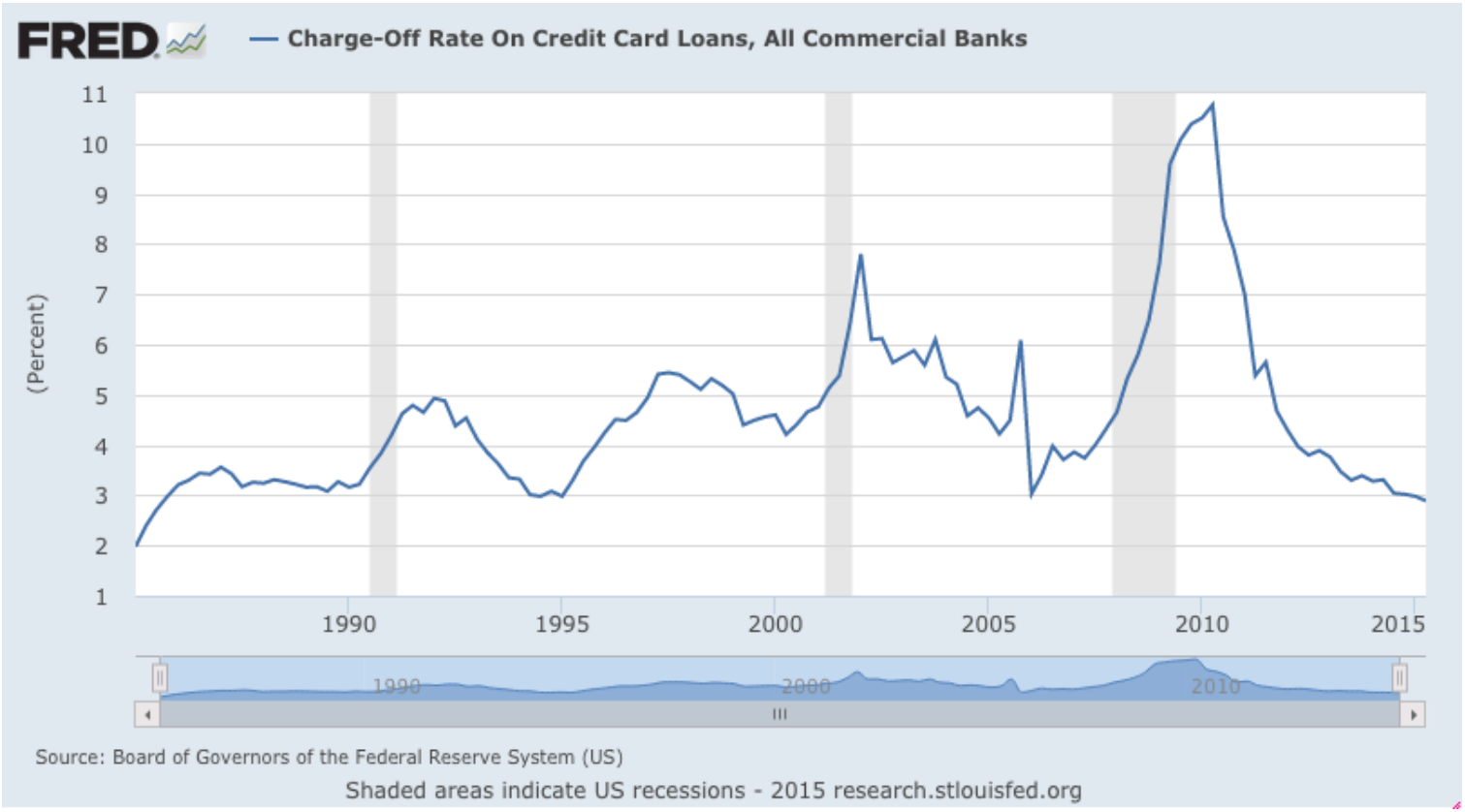
  - Butaru et al. (2015) learn models for predicting CC delinquency across several large banks (and compare risk management practices across banks).
- Many of these have a “horse race” element.
- One major issue is the Lucas Critique. Will get back to this...

Predicting Credit Card Delinquency

- Rapidly growing consumer credit market.
- High charge-off rate and severe delinquency rate during the financial crisis highlight the need for robust and improved out-of-sample prediction models for risk management



- With good predictions of delinquency, banks can actively manage credit to manage their exposure (Khandani, Kim, and Lo, 2010).

Project Overview

- Immediate goal: Support risk-based supervision
  - Compare performance of ML methods vs. “traditional” logistic regression.
  - Compare risk management across banks.
- Future goal: Measure systemic risk
  - Combine data across institutions.
  - Generate aggregate forecast models.
  - Use in stress testing?

Data Sources

- Credit card data
  - Detailed account-level characteristics (days past due, balance, utilization, FICO, etc.)
    - ⋆ Cannot link the accounts across individuals
  - Collected by a major US regulator
  - Entire credit card portfolios of 6 large banks
  - Monthly data starting from January 2008
- Attribute data
  - Detailed borrower characteristics from a credit bureau (linked by account)
  - Quarterly starting in 2009
- Macroeconomic variables
  - Collected from various sources (linked by account ZIP)
  - Employment data, HPI, average wages, average hours, etc.
- In total, many TB of raw data

Sample Description

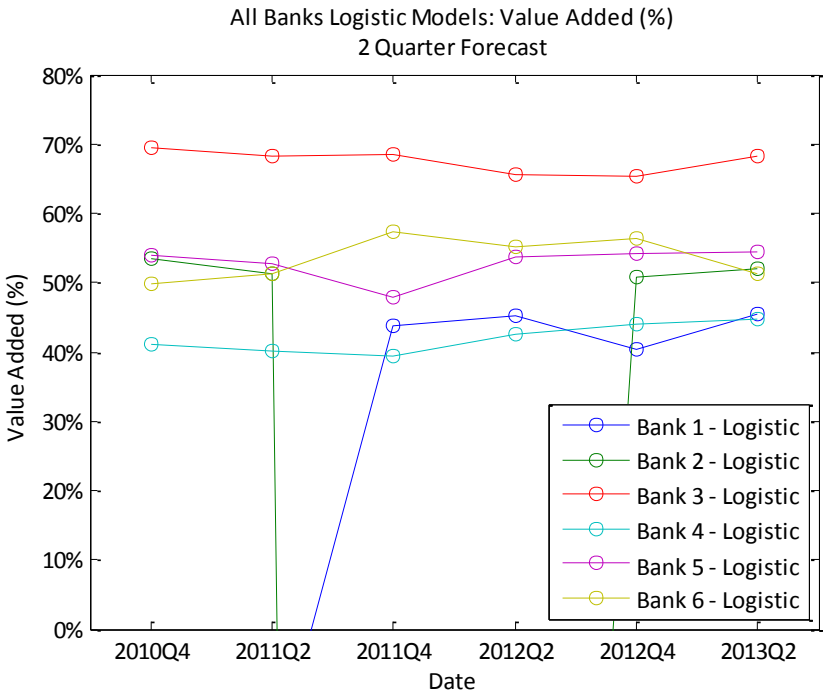
- Approx. 1% of each bank's CC portfolio.
- Yields between 90K and 1M observations per period per bank.
- Portfolio size varies over time (some grow, some decline) and the sample size is representative of the true portfolio.
- Substantial heterogeneity in the time series and cross-sectional distribution of delinquency rates.

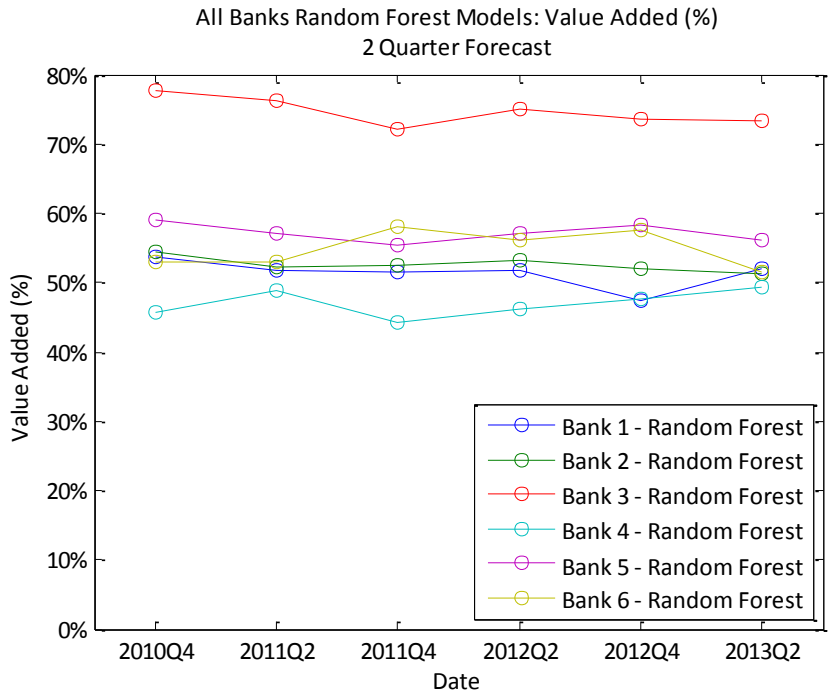
Modeling Dominates Credit Scores

Value-Added Analysis

- Compute a hypothetical cost-saving per customer, assuming the bank would cut lines of those predicted to default. Depends on:
  - Classification accuracy (the whole confusion matrix): **Quality of the model**
  - Run-up ratio (how much customers will increase their balance after time of prediction)
  - Profitability margin: Expected future cash-flows (opportunity cost of misclassification)
- Based on the framework of (Khandani, Kim, and Lo, 2010).

Value-Added Comparison





Most Important Attributes For Prediction

- Days past due
- Behavioral score
- Refreshed credit score
- Ratio of actual to minimum payents
- 1 month change in monthly utilization
- Payment equal to minimum in last 3 months

Further Insights

- Banks vary greatly in their risk management practices and effectiveness
  - 3 of the banks are very effective at cutting lines of accounts predicted to become delinquent
- Risk factors affecting delinquency vary across banks
- Macroeconomic variables affect different banks differently
  - Were more important factors in the model in 2012 and earlier than they are now.

Are Models For Predicting Failure Destined to Fail?

- So what if you can predict these things well in hindsight?
- The basic problem: Agent incentives and Goodhart's law (Wikipedia's formulation: "When a measure becomes a target, it ceases to be a good measure").
- If the ML model (or any risk model (Danielsson, 2002)) is part of the regulatory system, it will break down, because the data generating process will change.

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- If the ML model (or any risk model (Danielsson, 2002)) is part of the regulatory system, it will break down, because the data generating process will change.
- Rajan, Seru, and Vig (2015) study this empirically in the context of subprime mortgage loans originated from 1997–2006.
  - Securitization changes lenders' incentives and behavior. Over time, borrowers with similar "hard" information in the data become worse risks because they are worse along the "soft" information dimension (unobservable to investors).
  - "[When] incentive effects lead to a change in the underlying regime, the coefficients from a statistical model estimated on past data have no validity going forward, regardless of how sophisticated the model is or how well it fits the prior data."

Approach: Don't Share the Model

New York Times, "Not communicating to banks exactly what they need to do to get their bankruptcy plans to pass muster is frustrating, confusing and part of the plan."

TheUpshot

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GET THE UPSHOT IN YOUR INBOX

RULES, RULES

How Regulators Mess With Bankers' Minds, and Why That's Good

Peter Eavis @petereavis APRIL 14, 2016

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Bank regulators on Wednesday sent a message that big banks are still too big and too complex. They rejected special plans, called living wills, that the banks have to submit to show they can go through an orderly bankruptcy.

The thinking behind the regulators' call for living wills is that if a large bank crash is orderly, there will be no need to save it and no need for taxpayer bailouts.

Pretty straightforward, right? Not for the banks. The regulators deliberately did not communicate the exact things the banks needed to do for their plans to pass muster. In this way, they kept them on their toes — and treating powerful banks this way may end up playing a surprisingly important role in keeping the financial regulation effective over time.

Issues

- The regulatory model will still affect the system even if it doesn't explicitly change agent behavior
- Transparency can be important in many contexts
- Can the model be backed out from results?
- Not insurmountable in many applications

Approach: CS Work on Privacy and Fairness?

- Dwork, Hardt, et al. (2012) operationalize fairness
  - Given a (task-specific) similarity metric on individuals (can be designed by a regulator), the classifier must produce distributions on outcomes for these individuals that are bounded by a function of the distance between them.
  - Both they and Feldman et al. (2015) also consider statistical discrimination and disparate impact.
- Differential privacy (Dwork, McSherry, et al., 2006): Participation of a single person does not change the outcome significantly.
- While these ideas don't immediately generalize to the "model in the loop" problem, could there be a solution with a similar flavor?

Approach: Robust Control?

- Explicitly think about closed-loop control with the prediction algorithm in the loop.
- Combine a structural or causal model of agent decisions with a predictive model that also includes other observables (Rajan, Seru, and Vig, 2015).
- Could inform policy at a broader level.

Adoption of ML

- These problems are really not specific to using ML techniques. Banks and regulators already use models to predict the future. ML typically does it better.
- Not meant to replace causal models where needed.
- In practice, have to re-train models regularly to deal with nonstationarities.

Adoption of ML

- These problems are really not specific to using ML techniques. Banks and regulators already use models to predict the future. ML typically does it better.
- Not meant to replace causal models where needed.
- In practice, have to re-train models regularly to deal with nonstationarities.
- The myth of interpretability
  - Are logistic regression coefficients really meaningful?
  - Single decision trees are equivalent to sets of rules, but decision tree learners are inherently unstable. How meaningful is the tree?
  - Often used synonymously with “manually sanity checkable”
  - There are ways to sanity check more complex models as well (random forest feature scores, checking which features drive changed in NN output, etc.)

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Text Analysis

- Big idea: Ton of information in text that hasn't been quantified and analyzed, but could be usable.
- Examples:
  - Gentzkow and Shapiro (2010) measure ideological slant by identifying trigrams used much more frequently by Democrats or Republicans in the congressional record, and use this to estimate the drivers of media slant.

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  - Tetlock, Saar-Tsechansky, and Macskassy (2008) use fraction of negative words in firm-specific news stories to predict accounting earnings and stock returns.
  - Manela and Moreira (2016) construct a measure of aggregate uncertainty "News Implied Volatility" (NVIX). ML (SVR) to map from bag-of-bigrams representations of WSJ articles to VIX in the observed period, and can then generalize to before VIX existed.

Methods

- Keyword counting. Where do we get the keyword lists?
- Linear models (SVMs, regularized logistic regression)
  - Mallet (`http://mallet.cs.umass.edu/`) is a great toolbox!
- Word embeddings (e.g Word2vec) are hot (Mikolov et al., 2013).
- Deep models + word embeddings are promising, including for sentiment analysis (Santos and Gatti, 2014; Tang et al., 2014).
- Big question in many ML applications: where do we get the labels? (Now: Often crowdsourcing)
- Two big caveats: generalization across datasets and across time. Language changes fast!

Political Ideology Classification in ML/NLP

- Sentence and article level classification (vs. outlet level)
- Typically evaluated by cross-validation on the same corpus, or on very similar texts
- Would it be feasible to train on one data from one context (e.g. speeches in congress) and learn the bias of writers in another (e.g. Wikipedia)?

Recent Work on Political Ideology (wih Hao Yan and Allen Lavoie)

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- Congressional Record
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Year	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
Dem (CR)	14504	11134	17990	11053	14580	11080	11161	8540	9673	7956
Rep (CR)	11478	9289	12897	8362	13351	7878	9141	6841	8212	6585
Salon	1613	1561	2161	2598	2615	1650	1860	1630	865	123
Townhall	27	143	290	341	174	176	258	380	441	674
RationalWiki	0	0	302	514	666	854	1086	1208	1342	1402
Conservapedia	0	93	1752	2381	2933	3214	3467	3698	3792	3863

Algorithms

- Key Partisan Phrases (KPP): Following Gentzkow and Shapiro
- Logistic regression on n-grams (Bag-of-bigrams, TFIDF, feature hashing)
- Recursive autoencoder (RAE) (Socher et al., 2011).

Algorithms

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- Logistic regression on n-grams (Bag-of-bigrams, TFIDF, feature hashing)
- Recursive autoencoder (RAE) (Socher et al., 2011).
- N-gram methods outperform KPP in initial tests, while selecting similar looking bigrams, so we focus on the N-gram and RAE methods
- Some bigrams common to KPP and BOBLR for Democrats (left) and Republicans (right) in the 2005 Congressional Record

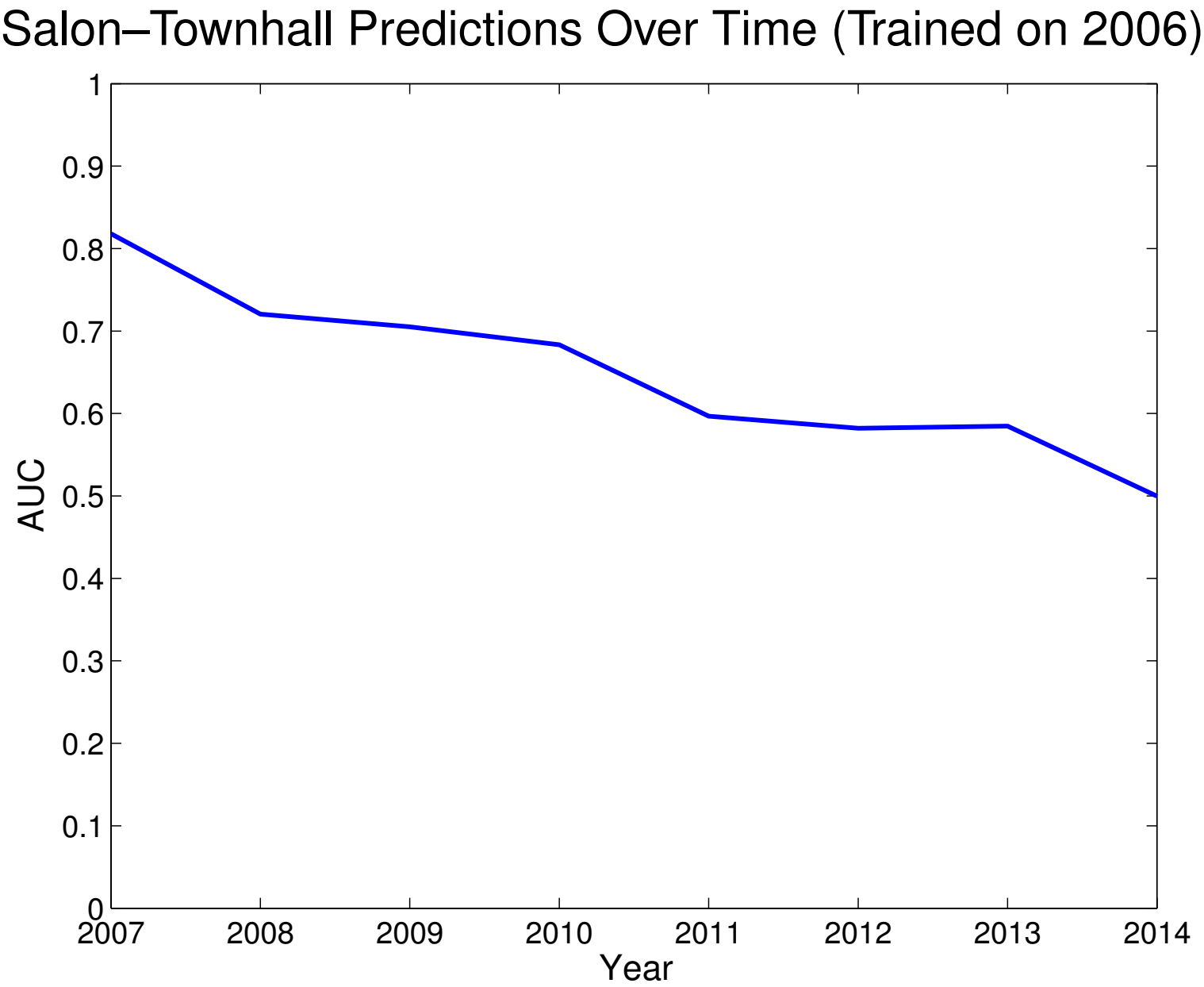
KPP	BOBLR
private account	privat account
tax break	tax break
oil compani	oil compani
trade deficit	trade deficit
nuclear option	nuclear option
middle class	middl class
budget cut	budget cut
cut medicaid	cut health
war iraq	iraq war
republican leader	republican leader
republican party	republican party
budget deficit	budget deficit

KPP	BOBLR
illegal alien	illeg alien
war terror	war terror
tax relief	tax relief
global war	global war
tax increase	tax increas
feder spending	feder spend
budget cut	budget cut
border security	secur border
war terrorism	war terror
iraqi people	iraqi peopl
create job	job creat
business owner	busi owner

Generalizing Across Datasets

Training \ Test	Cong. Rec.	Salon & Townhall	Wikis
Cong. Rec.	0.79 (LR) 0.78 (RAE)	0.63 (LR) 0.56 (RAE)	0.52 (LR) 0.46 (RAE)
Salon & Townhall	0.55 (LR) 0.54 (RAE)	0.81(LR) 0.93 (RAE)	0.54 (LR) 0.62 (RAE)
Wikis	0.50 (LR) 0.46 (RAE)	0.49 (LR) 0.58 (RAE)	0.80 (LR) 0.87 (RAE)

Generalizing Across Time



The Across-Dataset Problems Are Not Driven by Time

Testing and Averaging By Year

Training \ Test	Cong. Rec.	Salon & Townhall	Wikis
Cong. Rec.	0.82 (LR) 0.81 (RAE)	0.64 (LR) 0.59(RAE)	0.51 (LR) 0.47 (RAE)
Salon & Townhall	0.56 (LR) 0.54 (RAE)	0.91 (LR) 0.90 (RAE)	0.50 (LR) 0.55 (RAE)
Wikis	0.50 (LR) 0.47 (RAE)	0.54 (LR) 0.57 (RAE)	0.82 (LR) 0.82 (RAE)

Takeaways

- Must be very careful in generalizing across types of text, especially for short texts.
- Temporal change of language can be a big issue.
- Big pro for finance: there may be natural labels to exploit.
- Perhaps combining structural and textual information will help?
  - But even semantically rich embeddings can be problematic in the political context (e.g. “private accounts” vs. “personal accounts” for social security).

In Conclusion

- Machine learning is very good with:
  - Out-of-sample prediction.
  - Big data.
  - Nonlinear models.
  - “Not immediately quantitative” data (text, images)
- When these strengths speak well to a problem, it’s silly not to use the best techniques we have available!

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