A Bird-Eye view of Learning Theory

We want to design algorithms that take data as input and return predictions as output. But there are fundamental limits to our ability to predict and how quickly we can achieve good performance.

Two driving questions

- How well can we learn given very limited data?
- What are the computational challenges of prediction?
An Economic Translation

Thinking in terms of the economic tradeoffs, our goal is to determine the equilibrium point among the following:

- The marginal cost of additional data
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- The marginal cost of additional data
- The marginal value of performance improvement (i.e. better decision making)
- The marginal cost of computational resources
- The marginal value of time
Financialization of ML

In 6 Slides
1. Data Brokerage

In the world of Big Data, buying and selling information is a growing industry.
2. Algorithms as a Service

All-purpose ML algorithms are being provided as a web service and sold to developers.
3. Information Markets

Markets built entirely for speculative purposes, where traders can buy/sell securities on elections results to football matches, have flourished in recent years.
4. A Market for Cycles

There is an emerging competitive market where unit of computation are sold like a commodity

<table>
<thead>
<tr>
<th>vCPU</th>
<th>ECU</th>
<th>Memory (GiB)</th>
<th>Instance Storage (GB)</th>
<th>Linux/UNIX Usage</th>
</tr>
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<tr>
<td>m3.medium</td>
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<td>$0.070 per Hour</td>
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<tr>
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<td>8</td>
<td>26</td>
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<td>$0.560 per Hour</td>
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</table>
5. A Market for Solutions

Companies are starting to turn towards the *prize-driven competition* to solve big data challenges, rather than hiring in-house data scientists.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Team Name</th>
<th>Best Test Score</th>
<th>% Improved</th>
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<tbody>
<tr>
<td>1</td>
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<td>0.8567</td>
<td>10.06</td>
</tr>
<tr>
<td>2</td>
<td>The Ensemble</td>
<td>0.8567</td>
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</tr>
<tr>
<td>3</td>
<td>Grand Prize Team</td>
<td>0.8582</td>
<td>9.90</td>
</tr>
<tr>
<td>4</td>
<td>Opera Solutions and Vandelav United</td>
<td>0.8588</td>
<td>9.84</td>
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</tbody>
</table>
6. Market for Academics

ML Practitioners (including many academics and graduate students) have apparently risen in value in recent years.
This Talk

We will discuss some recent results connecting learning-theoretic ideas to finance and economic questions.

- Intro
- Quick review of regret minimization
- Regret in the context of market making
- Exponential family distributions viewed as a prediction market mechanism
The Typical Regret-minimization Framework

We imagine an online game between Nature and Learner. Learner has a (typically convex) decision set $\mathcal{X} \subset \mathbb{R}^d$, and Nature has an action set $\mathcal{Z}$, and there is a loss function $\ell : \mathcal{X} \times \mathcal{Z} \rightarrow \mathbb{R}$ defined in advance.
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Online Convex Optimization

For $t = 1, \ldots, T$:

- Learner chooses $x_t \in \mathcal{X}$
- Nature chooses $z_t \in \mathcal{Z}$
- Learner suffers $\ell(x_t, z_t)$

Learner is concerned with the regret:

$$\sum_{t=1}^{T} \ell(x_t, z_t) - \min_{x \in \mathcal{X}} \sum_{t=1}^{T} \ell(x, z_t)$$
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This talk we assume $\ell$ is linear in $x$; WLOG $\ell(x_t, z_t) = x^T z_t$. 
Follow the Regularized Leader

FTRL – Primal Version

1: Input: learning rate $\eta > 0$, regularizer $R : \mathcal{X} \rightarrow \mathbb{R}$

2: for $t = 1 \ldots T$, $x_t \leftarrow \arg \min_{x \in \mathcal{X}} R(x) + \eta \sum_{s=1}^{t-1} x^\top l_s$. 

FTRL is essentially the “only” algorithm we have. (This COLT: even Follow the Perturbed Leader is a special case of FTRL [Abernethy, Lee, Sinha, and Tewari, 2014b].)
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Regret Bounds on FTRL

Theorem (now classical)

Let $l_1, \ldots, l_T$ be an arbitrary sequence of vectors, and let $L_t := l_1 + \ldots + l_t$. Assume $R(x_0) = 0$. Then

$$\text{Regret}_T \leq \frac{R(x^*)}{\eta} + \sum_{t=1}^{T} D_R(x_t, x_{t+1})$$

$$\leq \frac{R(x^*)}{\eta} + \eta \sum_{t=1}^{T} (x_t - x_{t+1})^T l_t$$

$$\implies \text{Regret}_T \leq O \left( \sqrt{\sum_{t=1}^{T} \|l_t\|^2} \right)$$

where $D_R(\cdot, \cdot)$ is the Bregman divergence w.r.t. $R$, and the last line follows from tuning $\eta$ and assuming some curvature properties of $R$. 
Market Making as Regret Minimization

A lot of the big money in finance is made through *market making*: a market maker (MM) is an agent always willing to buy *and* sell shares/securities at sequentially-set prices.
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- MM sets bid and ask prices \( \overline{p}_t, p_t \in \mathbb{R}_+ \)
- A trader purchases \( r_t \in \mathbb{R} \) shares (short sale \( \equiv r_t < 0 \))
- MM receives \( g_t = \$\overline{p}_t r_t \) if \( r_t > 0 \) or \( g_t = \$p_t r_t \) if \( r_t \leq 0 \)
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All shares eventually liquidate at a price of $p^*$.

$$\text{Loss of MM} = \sum_{t=1}^{T} r_t p^* - \sum_{t=1}^{T} r_t (\bar{p}_t 1[r_t > 0] + p_t 1[r_t \leq 0])$$

(More at Abernethy and Kale [2013])
Market Making for Complex Security Spaces

Often we want to sell shares in multiple related securities and we want to price these securities jointly.

- Traders can purchase bundles of shares \( r \in \mathbb{R}^d \).
- Payout function \( \phi : \mathcal{X} \rightarrow \mathbb{R}^d \).
- In event of \( x \), payout for purchasing bundle \( r \) is \( r^T \phi(x) \).

The canonical pricing strategy, which has now been well-studied, is the following:

- Construct a convex \( C : \mathbb{R}^d \rightarrow \mathbb{R} \) in order that \( \{\nabla C\} \) coincides with the rel.int. of Hull(\( \{\phi(x) : x \in \mathcal{X}\} \)).
- Market maker maintains cumulative outstanding share vector \( q \), announces marginal price vector \( \nabla C(q) \).
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Market Making $\simeq$ Online Learning

How to construct $C$? Choose a “liquidity function” $R : \text{Hull} \left( \{ \phi(x) : x \in \mathcal{X} \} \right) \rightarrow \mathbb{R}$, and let

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With this connection, we get a set of natural equivalences:

Market Making $\approx$ Online Learning

Market Maker Loss $\approx$ Learning Regret

Seq. Pricing Strat. $\approx$ FTRL

Liquidity at price $p$ $\approx$ $\nabla^2 R(p)$

Please see Chen and Vaughan [2010] and Abernethy, Chen, and Vaughan [2013] for details.
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Let's now switch gears and see how exp families relate can be viewed through an entirely probability-free lens.
Exponential Family Distributions

Many dist. families we encounter are exponential families. Let $\beta \in \mathbb{R}^d$ be params, $\phi: \mathcal{X} \to \mathbb{R}^d$ some "statistics". The pdf of dist. corresponding to $\beta$ is

$$P_\beta(x) \propto \exp(\beta^T \phi(x))$$

For $x \in \mathcal{X}$:
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\text{For } x \in \mathcal{X} : \quad P_{\beta}(x) = \exp(\beta^T \phi(x) - \Psi(\beta))
\]

Where

\[
\Psi(\beta) = \log \int_{\mathcal{X}} \exp(\beta^T \phi(x')) dx'
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- $\phi(x)$ is called the “sufficient statistics” of $x$
- $\Psi(\beta)$ is called the “log partition function”
- A wonderful fact: $\mathbb{E}_{X \sim P_{\beta}}[\phi(X)] = \nabla \Psi(\beta)$
Forget That: Exponential Family Market

Imagine \( x \in \mathcal{X} \) is some future uncertain outcome, and a firm wants predictions on \( \phi(x) \).
Forget That: Exponential Family Market

- Imagine $x \in \mathcal{X}$ is some future uncertain outcome, and a firm wants predictions on $\phi(x)$.
- Firm will create a *prediction market*
- Prices should correspond to aggregate belief

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- The firm will sell bundles of shares $\delta \in \mathbb{R}^d$ to trader
- Upon outcome $x$, reward for purchasing $\delta$:

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- Upon outcome $x$, reward for purchasing $\delta$:
  \[ \text{payoff}(\delta|x) = \phi(x) \top \delta \]

- Let sum of all outstanding shares be $\Theta := \delta_1 + \ldots + \delta_m$.
- The price of buying $\delta$:
  \[ \Psi(\Theta + \delta) - \Psi(\delta) \]
Benefits of the Market Interpretation

- Given that $\Theta$ represents market state

  \[ \text{Marginal prices} = \nabla \psi(\Theta), \]

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- If the true distribution over $x$ is $Q$, then
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- FIRM has to pay
  
  $$\mathbb{E}_{\text{FirmCost}}(\Theta_{\text{final}}) = KL(Q; P_0) - KL(Q; P_{\Theta_{\text{final}}})$$

(Results in Abernethy, Kutty, Lahaie, and Sami [2014a])
Interpreting Market Behavior

Let us imagine traders in such a market that has a belief on the outcome $x$ distributed according to $P_\beta$. Assume trader has *exponential utility* (with risk-aversion param $a$):

$$\text{Utility}($99) = 1 - \exp(-a \cdot 99)$$
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Buying $\delta$ shares $\iff$ updating belief $\beta \leftarrow \beta + \delta$
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**Proposition: Equilibrium \( \equiv \) MAP-estimate for Gaussian**

Assume we have \( n \) traders with belief parameters \( \beta_1, \ldots, \beta_n \) with risk aversion parameters \( a_1, \ldots, a_n \). If they all trade to maximize expected utility, then *in equilibrium* we have:

\[
\text{EquilibriumState } \Theta_{\text{final}} := \frac{\Theta_{\text{init}} + \sum_i \beta_i a_i^{-1}}{1 + \sum_i a_i^{-1}}
\]
The Vision

We would have a number of major benefits if we were able to cast a broader class of ML algorithms through the lens of market equilibria.

- Robustness on solution
- *Real* decentralization of learning tasks
- Possible model for distributed computing
Learning, Markets, and Exponential Families

Intro: Economics

Learning ≈ Tradeoffs

Financialization of ML

Outline:

Market Making ≈ OLO

Exp. Families ≈ Markets

Jacob Abernethy


