0000 0000 0000 0000 0000 0000	Prologue	The Stochastic Model	Stationarity	Machine Learning	Conclusion

# Interpreting Prediction Markets: a Stochastic Approach

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Joint work with Nicolás Della Penna and Mark Reid

Prologue 00000	The Stochastic Model	Stationarity	Machine Learning	Conclusion





# Work done while visiting ANU + NICTA

Prologue ●oooo	The Stochas	tic Model	Stationa 0000	rity	Machine Lear	ning	Conclusion
Standard	Predi	ction Mar	ket				
		Obama \$1		Romney \$1	/		
		\$0.54		\$0.46			

- Traders buy and sell contracts
- Prices fluctuate as demand changes
- Prices should reflect "consensus estimate"

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What is this?
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- Traders buy and sell contracts
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What is this in terms of the traders' beliefs?
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Prologue o●ooo	The Stochastic Model	Stationarity 0000	Machine Learning	Conclusion
Answer fr	om Standard T	heory		

# If traders have unbounded wealth and are risk neutral, prices = **last traders' belief**

If traders perform proper Bayesian updating, prices = **posterior** given everyone's private info

Big If's!!

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Prologue oo●oo	The Stochastic Model	Stationarity 0000	Machine Learning	Conclusion		
Standard Equilibrium Analysis						

# Setting:

- Look at the *distribution P* of traders' beliefs
- Fix some price  $\pi$  of contract 1, say
- Look at total demand for that price
- Equilibrium is  $\pi^*$  s.t. supply = demand:

$$\int_0^1 \operatorname{demand}(\pi^*, p) \, d\mathcal{P}(p) = 0$$

Note: demand for Obama = supply for Romney

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Standard	Equilibrium An	alysis: Res	ults	

Manski, 2004:

**E** Risk neutral traders  $\implies \pi^* = \text{quantile of } \mathcal{P}$ 

Equilibrium point ("Manski point"):  $\pi^*$  such that

$$\frac{\int_0^{\pi^*} \mathcal{P}(p) dp}{1 - \pi^*} = \frac{\int_{\pi^*}^1 \mathcal{P}(p) dp}{\pi^*} \implies \int_{\pi^*}^1 \mathcal{P}(p) dp = \pi^*$$

Wolfers and Zitzewitz, 2006:

Kelly bettor: demand = 
$$\frac{W}{\pi} \frac{p - \pi}{1 - \pi}$$
 *linear in p*

• Kelly bettors  $\implies \pi^*$  = mean of  $\mathcal{P}$ 

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# Standard Equilibrium Analysis: Really?



Where is the equilibrium? How do we use these prices to make predictions?



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# Standard Equilibrium Analysis: Really?



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Prologue	The Stochastic Model ●○○○	Stationarity 0000	Machine Learning	Conclusion
A Stocha	stic Approach			

Based on Othman and Sandholm, 2010:

- Look at a sequential market model
- Sample traders repeatedly from  $\mathcal{P}$
- Each trades one-by-one in the market
- The current prices adjust to trades ... using an automated market maker

Prologue 00000	The Stochastic Model	Stationarity 0000	Machine Learning	Conclusion
The Marl	ket Maker			

Use model of Abernethy, Chen, Vaughan (2011)

- n mutually exclusive events
- Convex function  $C : \mathbb{R}^n \to \mathbb{R}$
- Current quantity  $q \in \mathbb{R}^n$
- Trade of  $d \in \mathbb{R}^n$  costs C(q + d) C(q)
- Prices:  $\nabla C(q)$

#### Example: exponential weights

$$C(q) = \log\left(\sum_{i} \exp(q_i)\right) \qquad \nabla C(q_i) = \frac{\exp(q_i)}{\sum_{j} \exp(q_j)}$$

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The Der	nands			



 $d_i$  is the demand for contract i

Prologue 00000	The Stochastic Model 000●	Stationarity 0000	Machine Learning	Conclusion
The Ful	l Model			

For t = 1 ... T:

- Draw a trader (p, W) from  $(\mathcal{P}, \mathcal{W})$  *i.i.d.*
- Trader buys bundle  $d(W, \pi_t, p)$

Price adjusts:

$$\pi_{t+1} \leftarrow \nabla C \Big( (\nabla C)^{-1}(\pi_t) + d(W, \pi_t, \rho) \Big)$$

Prologue	The Stochastic Model	Stationarity ••••	Machine Learning	Conclusion
The Stati	onary Point			

# First question: what is the "fixed point" of our process?

When does  $\mathbb{E}[\pi_{t+1}] = \pi_t$ ?

Define  $\pi^s$  to be this stationary point

Prologue	The Stochastic Model	Stationarity ●000	Machine Learning	Conclusion
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Stationarity and Equilibrium				

How does this  $\pi^s$  relate to the equilibrium  $\pi^*$ ?

Othman and Sandholm:

Binary market
Risk neutral traders
Each invest 
$$\epsilon$$
 at a time
 $\Rightarrow$   $\pi^s = \pi^*$ 

Prologue	The Stochastic Model	Stationarity 0000	Machine Learning	Conclusion
Stationari	tv and Equilibri	um: Our M	odel	

# Is this a general phenomenon?

Does  $\pi^s = \pi^*$  in our more general model?

#### Theorem 1

For very general demands  $d, \pi^s \rightarrow \pi^*$  as  $W \rightarrow 0$ 

Obtain Othman and Sandholm result as a corollary

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Prologue	The Stochastic Model	Stationarity 0000	Machine Learning	Conclusion
Fixed vs.	Continuous Pr	ices		

# Same demands for both equilibrium and market-maker settings

fixed continuous

Open question: does Theorem 1 hold with more sensible demands?



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Prologue 00000	The Stochastic Model	Stationarity 0000	Machine Learning ●੦੦੦	Conclusion	
Market Making and Online Learning					

Chen and Vaughan, 2009: Market maker update = FTRL

Follow the Regularized Leader:

- Losses  $l_t \in \mathbb{R}^n$
- Actions  $\mathbf{w}_t \in \Delta_n$
- Convex regularizer R

• 
$$\mathbf{w}_{t+1} \leftarrow \operatorname{argmin}\left\{\sum \ell_t \cdot \mathbf{w} + R(\mathbf{w})\right\}$$

Regret:

$$\sum_{t} \boldsymbol{\ell}_t \cdot \boldsymbol{w}_t - \min_i \left( \sum_{t} \boldsymbol{\ell}_t \right)_i$$

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Important caveat: final loss terms do not match up completely

FTRL regret 
$$\sum_{t} \ell_{t} \cdot \mathbf{w}_{t} - \min_{i} \left( \sum_{t} \ell_{t} \right)_{i}$$
Market Maker gain  $C\left( \sum_{t} d_{t} \right) - C(0) - \max_{i} \left( \sum_{t} d_{t} \right)_{i}$ 

Observation: They do line up in the fixed price model!  $d_t = -l_t$ 



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FTRL regret 
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Market Maker gain 
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$$\sum_{t} d_{t} \cdot \pi_{t}$$

Observation: They *do* line up in the fixed price model!  $d_t = -\ell_t$ 

Prologue	The Stochastic Model	Stationarity 0000	Machine Learning oo●o	Conclusion
FTRL → Mirror Descent				

Observation: If losses are *gradients*, FTRL = Mirror Descent

 $\ell_{t+1} = \nabla f(\mathbf{w}_t)$ 

And stochastic gradients → Stochastic Mirror Descent (SMD)

 $\ell_{t+1} = \nabla F(\mathbf{w}_t; \boldsymbol{\xi})$ 

Theorem 2

If demands are (negative) gradients

 $d(W, \pi, p) = -\nabla F(\pi; p, W),$ 

our stochastic update is an SMD of

 $f(\pi) := \mathbb{E}[F(\pi; W, p)].$ 

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Application: Kelly Bettors				

Back to Kelly bettors:

$$d(W,\pi,p)=\frac{W}{\pi}\frac{p-\pi}{1-\pi}$$

(note: fixed-price model)

Can write d as a gradient of  $F(\pi; W, p) := W \cdot KL(p, \pi)$ 

### Corollary

The stochastic model with Kelly bettors is an SMD of

$$f(\pi) := \overline{W} \cdot KL(\overline{p}, \pi)$$

Note: generalizes Wolfers and Zitzewitz by Theorem 1!

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Back to Interpreting Prediction Markets								

SMD has optimization guarantees:

Theorem (Duchi, Shalev-Shwartz, Singer, Tewari)

If  $\|\nabla F(\pi; p)\|^2 \leq G^2$  for all  $p, \pi$ , and R is  $\sigma$ -strongly convex, then with probability  $1 - \delta$ ,

$$f(\overline{\pi}_T) \leq \min_{\pi} f(\pi) + \left(\frac{D^2}{\eta T} + \frac{G^2 \eta}{2\sigma}\right) \left(1 + 4\sqrt{\log \frac{1}{\delta}}\right)$$

Time-averaged price!

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Back to I	nterpreting P	rediction Mar	kets	

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Time-averaged price!



So perhaps one should average market prices to form predictions



Particularly for volitile markets

Trade number



- Sensible demands for stationarity (Theorem 1)
- Using results on *learning rates* to set market *liquidity*
- Try on real market data!



Square loss of price to mean belief for State 9

Trades

 blogue
 The Stochastic Model
 Stationarity

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Machine Learning

Conclusion ○○○●

# thank you