Counterfactual evaluation of machine learning models

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Stripe

Stripe

- APIs and tools for commerce and payments

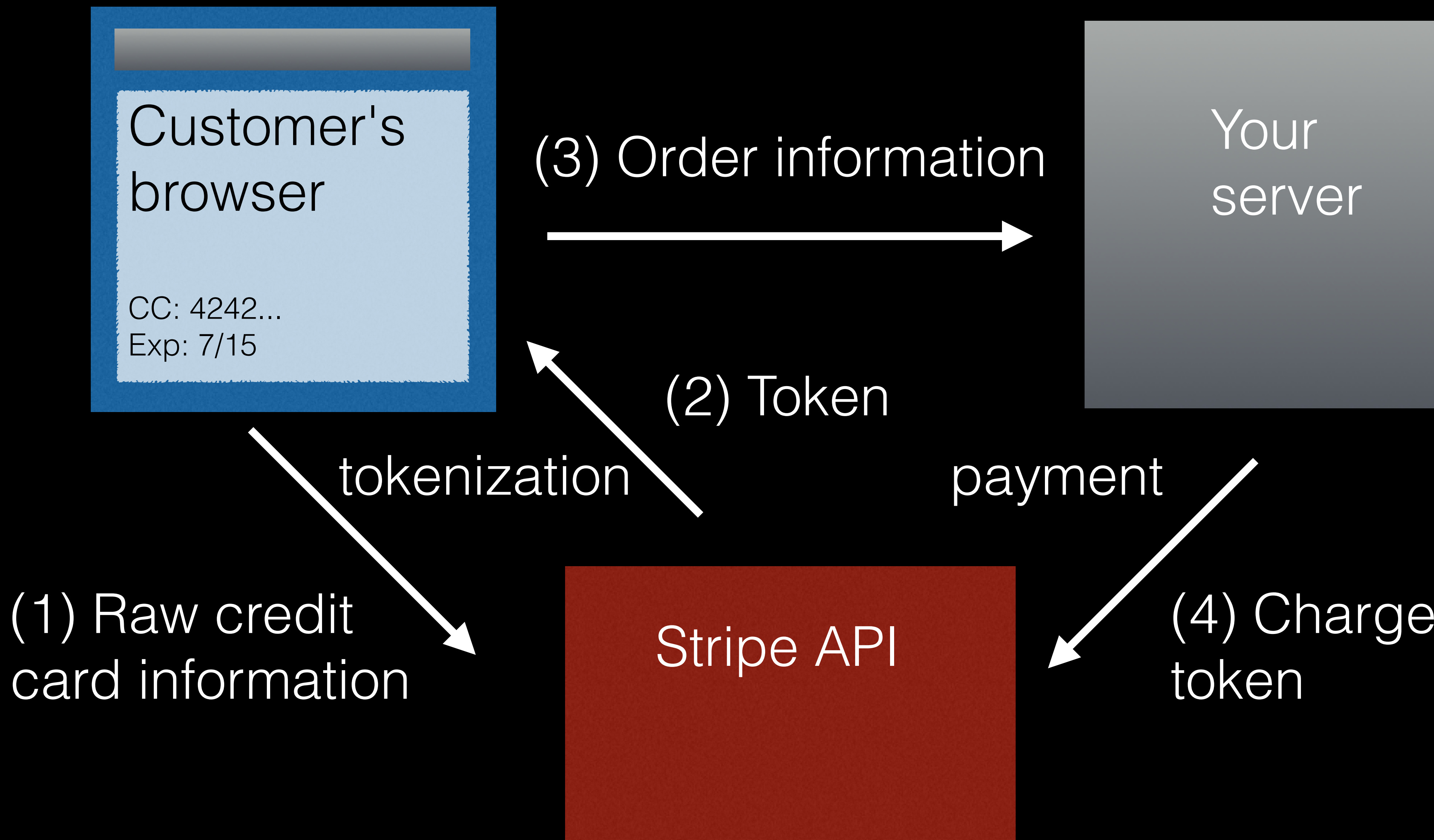
```python
import stripe
stripe.api_key = "sk_test_BQokiaJOvBdiI2HdlWgHa4ds429x"

stripe.Charge.create(
  amount=40000,
  currency="usd",
  source={
    "number": '4242424242424242',
    "exp_month": 12,
    "exp_year": 2016,
    "cvc": "123"
  },
  description="PyData registration for mlm@stripe.com"
)
```

Machine Learning at Stripe

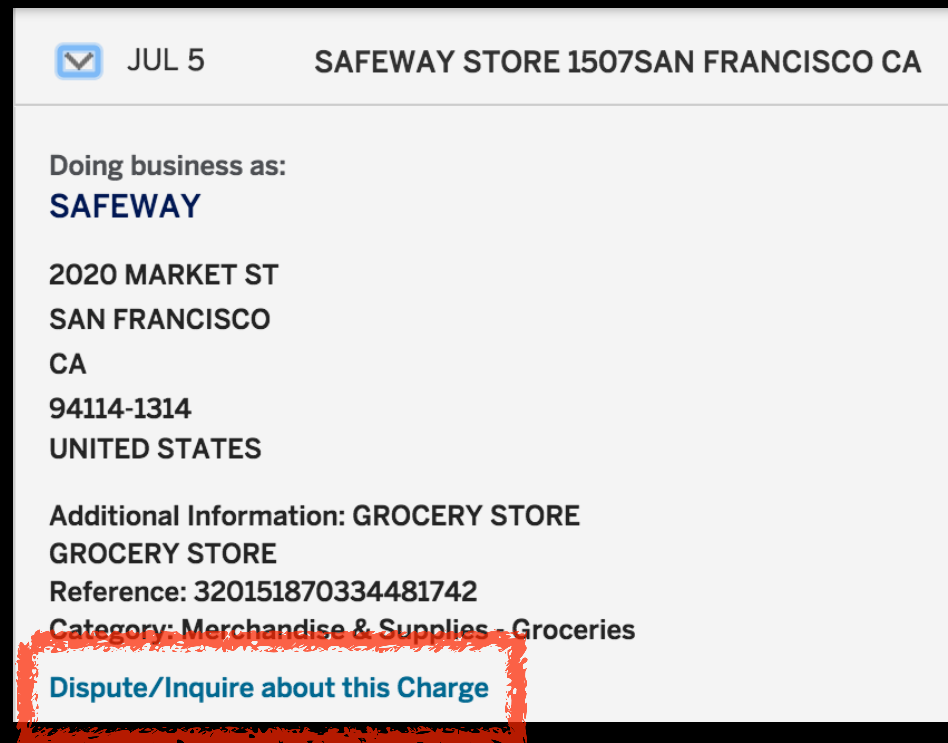
- Ten engineers/data scientists as of July 2015 (no distinction between roles)
- Focus has been on fraud detection
  - Continuous scoring of businesses for fraud risk
  - **Synchronous classification of charges as fraud or not**

Making a Charge



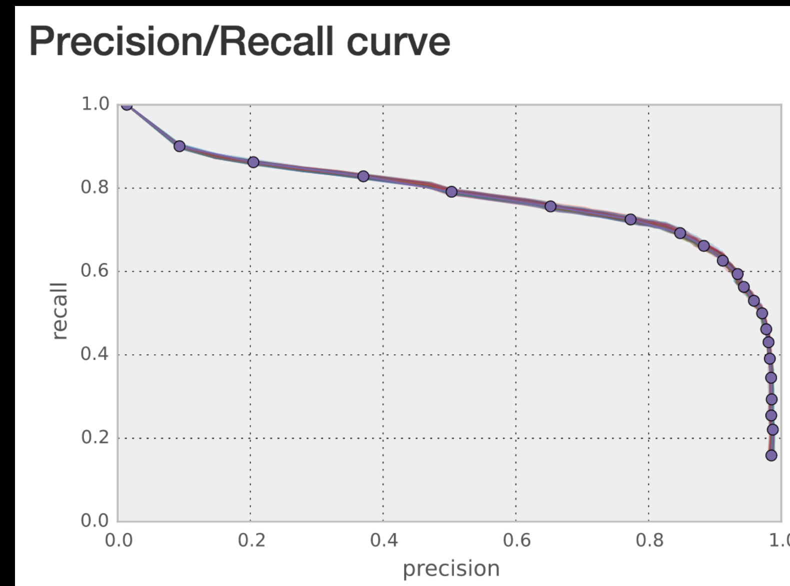
Charge Outcomes

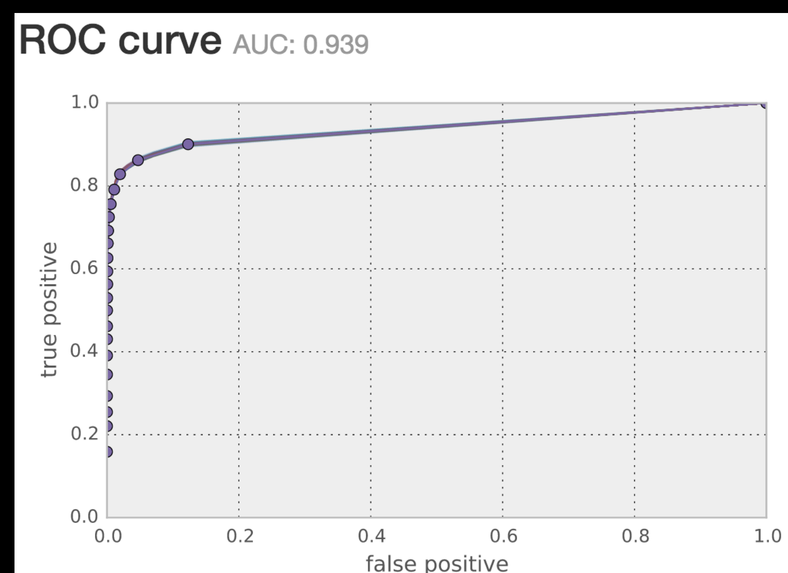
- Nothing (best case)
- Refunded
- **Charged back ("disputed")**
    - Fraudulent disputes result from "card testing" and "card cashing"
    - **Can take > 60 days to get raised**



Model Building

- December 31st, 2013
    - Train a **binary classifier** for **disputes** on data from Jan 1st to Sep 30th
    - Validate on data from Oct 1st to Oct 31st (need to wait ~60 days for labels)
- Based on validation data, pick a policy for actioning scores: block if **score > 50**



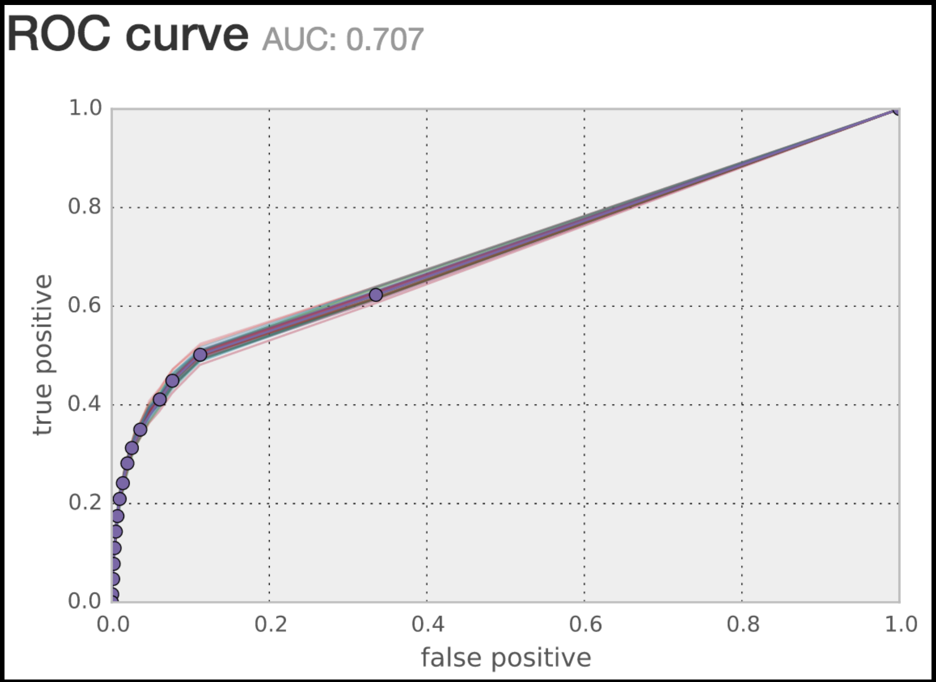


Questions

- Validation data is > 2 months old. How is the model doing?
- What are the **production** precision and recall?
- Business complains about high false positive rate: what would happen if we changed the policy to "block if **score > 70**"?

Next Iteration

- December 31st, 2014. We repeat the exercise from a year earlier
  - Train a model on data from Jan 1st to Sep 30th
  - Validate on data from Oct 1st to Oct 31st (need to wait ~60 days for labels)
  - Validation results look ~ok (but not great)



Next Iteration

- We put the model into production, and the results are terrible
  - From spot-checking and complaints from customers, the performance is worse than even the validation data suggested
- What happened?

Next Iteration

- We already had a model running that was blocking a lot of fraud
- Training and validating only on data for which we had labels: charges that the existing model didn't catch
- Far fewer examples of fraud in number. Essentially building a model to catch the "hardest" fraud
- Possible solution: we could run both models in parallel...

Evaluation and Retraining Require the Same Data

- For **evaluation**, **policy changes**, and **retraining**, we want the same thing:
  - An approximation of the distribution of charges and outcomes that would exist in the absence of our intervention (blocking)

First attempt

- Let through some fraction of charges that we would ordinarily block

```
if score > 50:
  if random.random() < 0.05:
    allow()
  else:
    block()
```

- Straightforward to compute **precision**

Recall

1,000,000 charges	Score < 50	Score > 50
Total	900,000	100,000
Not Fraud	890,000	1,000
Fraud	10,000	4,000
Unknown	0	95,000

- Total "caught" fraud = (4,000 * 1/0.05)
- Total fraud = (4,000 * 1/0.05) + 10,000
- Recall = 80,000 / 90,000 = **89%**

Training

- Train only on charges that were not blocked
- Include weights of 1/0.05 = 20 for charges that would have been blocked if not for the random reversal

```
from sklearn.ensemble import \
RandomForestRegressor
...
r = RandomForestRegressor(n_estimators=10)
r.fit(X, Y, sample_weight=weights)
```

Training

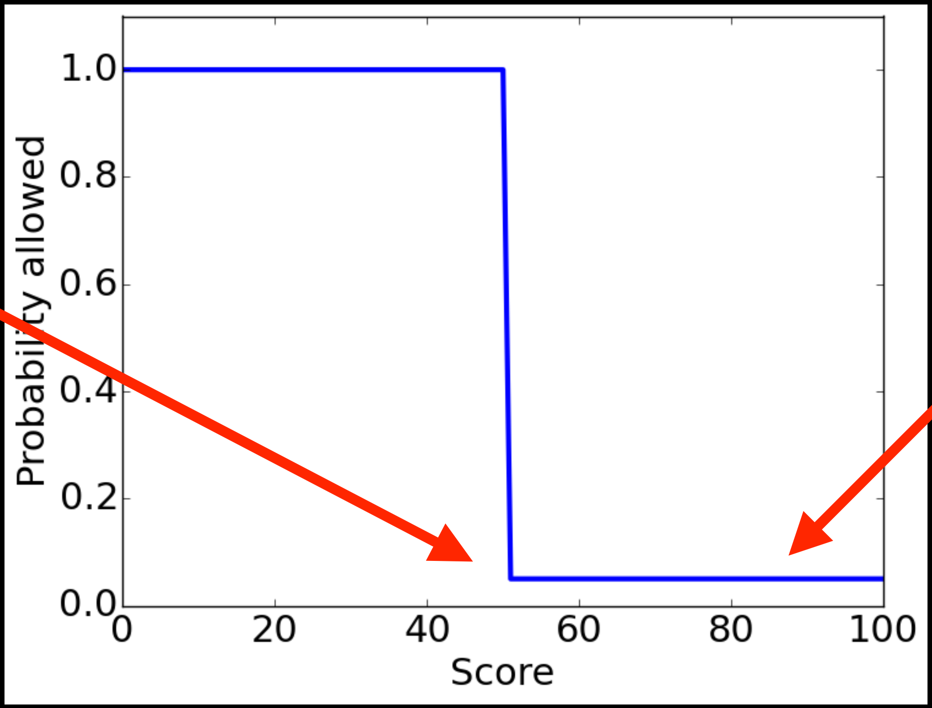
- Use weights in validation (on hold-out set) as well

```
from sklearn import cross_validation
X_train, X_test, y_train, y_test = \
  cross_validation.train_test_split(
    data, target, test_size=0.2)
r = RandomForestRegressor(...)
...
r.score(
  X_test, y_test, sample_weight=weights)
```

Better Approach

- We're letting through 5% of all charges we think are fraudulent. Policy:

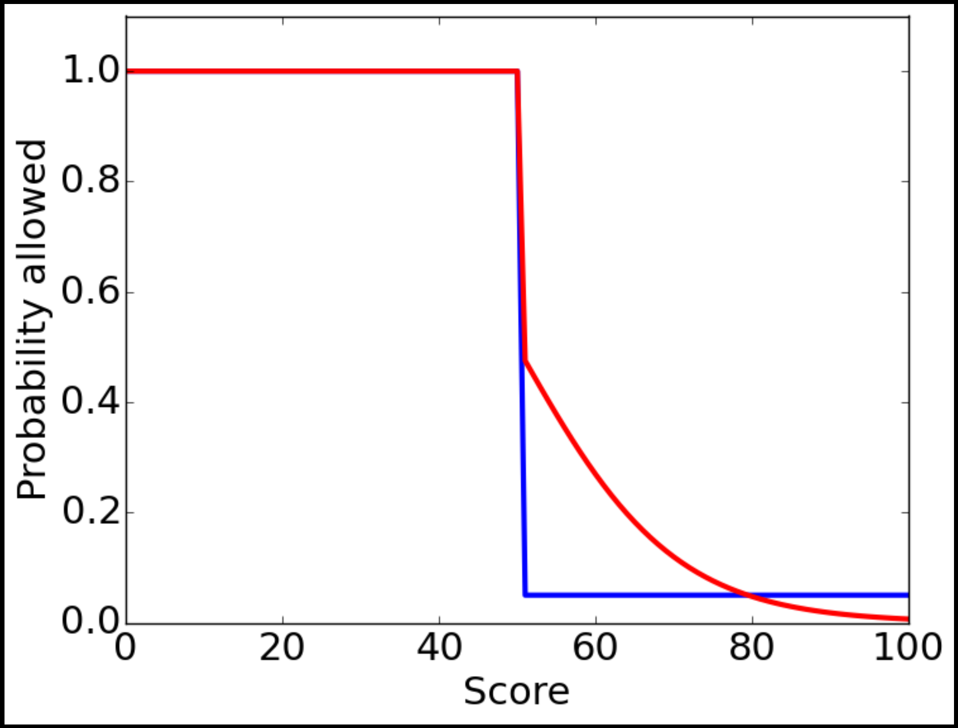
Could go either way



Very likely to be fraud

Better Approach

- **Propensity function**: maps classifier scores to P(Allow)
- The higher the score, the lower probability we let the charge through
- Get information on the area we want to improve on
- Letting through less "obvious" fraud ("budget" for evaluation)



Better Approach

```
def propensity(score):
  # Piecewise linear/sigmoidal
  ...
ps = propensity(score)
original_block = score > 50
selected_block = random.random() < ps
if selected_block:
  block()
else:
  allow()
log_record(
  id, score, ps, original_block,
  selected_block)
```

ID	Score	p(Allow)	Original Action	Selected Action	Outcome
1	10	1.0	Allow	Allow	OK
2	45	1.0	Allow	Allow	Fraud
3	55	0.30	Block	Block	-
4	65	0.20	Block	Allow	Fraud
5	100	0.0005	Block	Block	-
6	60	0.25	Block	Allow	OK

Analysis

- In any analysis, we only consider samples that were **allowed** (since we don't have labels otherwise)
- We weight each sample by **1 / P(Allow)**
    - cf. weighting by 1/0.05 = 20 in the uniform probability case

ID	Score	P(Allow)	Weight	Original Action	Selected Action	Outcome
1	10	1.0	1	Allow	Allow	OK
2	45	1.0	1	Allow	Allow	Fraud
4	65	0.20	5	Block	Allow	Fraud
6	60	0.25	4	Block	Allow	OK

Evaluating the "block if **score > 50**" policy

Precision = 5 / 9 = **0.56**
Recall = 5 / 6 = **0.83**

ID	Score	P(Allow)	Weight	Original Action	Selected Action	Outcome
1	10	1.0	1	Allow	Allow	OK
2	45	1.0	1	Allow	Allow	Fraud
4	65	0.20	5	Block	Allow	Fraud
6	60	0.25	4	Block	Allow	OK

Evaluating the "block if **score > 40**" policy

Precision = 6 / 10 = **0.60**
Recall = 6 / 6 = **1.00**

ID	Score	P(Allow)	Weight	Original Action	Selected Action	Outcome
1	10	1.0	1	Allow	Allow	OK
2	45	1.0	1	Allow	Allow	Fraud
4	65	0.20	5	Block	Allow	Fraud
6	60	0.25	4	Block	Allow	OK

Evaluating the "block if **score > 62**" policy

Precision = 5 / 5 = **1.00**
Recall = 5 / 6 = **0.83**

Analysis

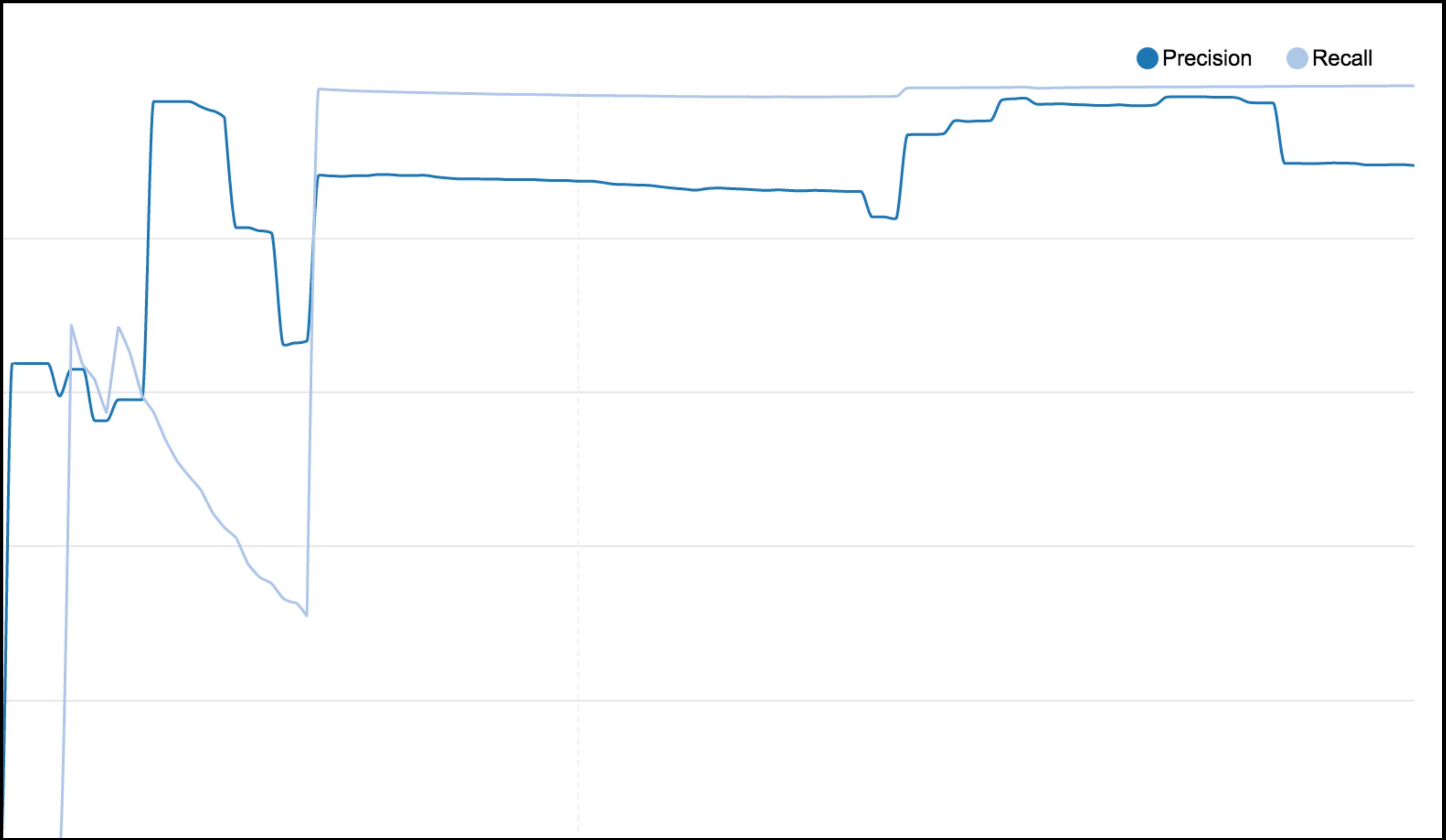
- The propensity function controls the "exploration/exploitation" payoff
- Precision, recall, etc. are estimators
    - Variance of the estimators <u>decreases</u> the <u>more</u> we allow through
- Bootstrap to get error bars (pick rows from the table uniformly at random with replacement)

New models

- Train on weighted data
  - Weights => approximate distribution without any blocking
- Can test arbitrarily many models and policies offline
- Li, Chen, Kleban, Gupta: "Counterfactual Estimation and Optimization of Click Metrics for Search Engines"

Technicalities

- Independence and random seeds
- Application-specific issues


Precision
Recall

Conclusion

- If some policy is actioning model scores, you can inject randomness in production to understand the counterfactual
- Instead of a "champion/challenger" A/B test, you can evaluate arbitrarily many models and policies in this framework

Thanks!

- Work by Ryan Wang (@ryw90), Roban Kramer (@robanhk), and Alyssa Frazee (@acfrazee)



- We're hiring engineers/data scientists!

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