Machine Learning Systems Design

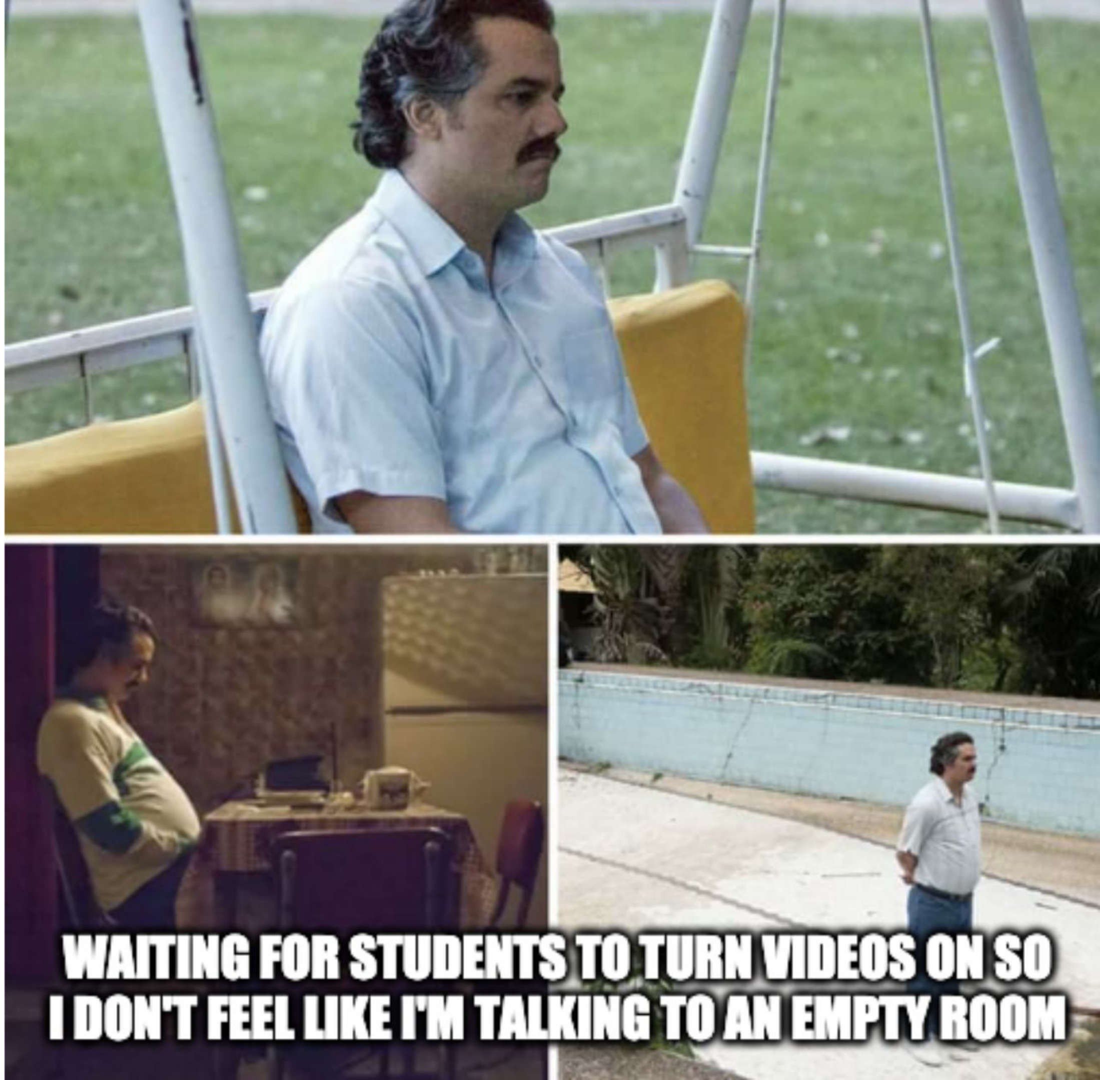
Lecture 10: Data Distribution Shifts & Monitoring

Stanford University

Zoom etiquettes

We appreciate it
if you keep videos on!

- More visual feedback for us
  to adjust materials
- Better learning environment
- Better sense of who you're with
  in class!



Agenda

1. Natural labels & feedback loops
2. Causes of ML failures
3. Breakout exercise
4. Data distribution shifts
5. Monitoring & observability

Lecture note is on course website / syllabus

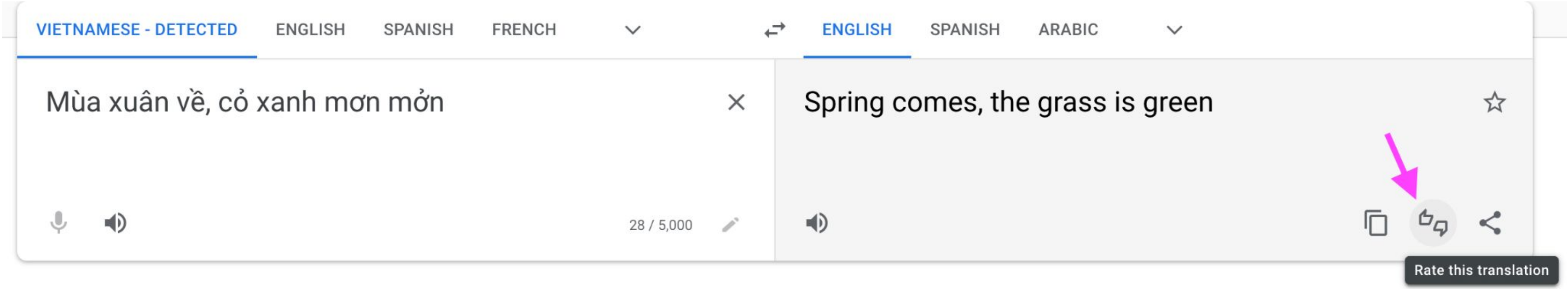
Natural labels & feedback loops

Natural labels

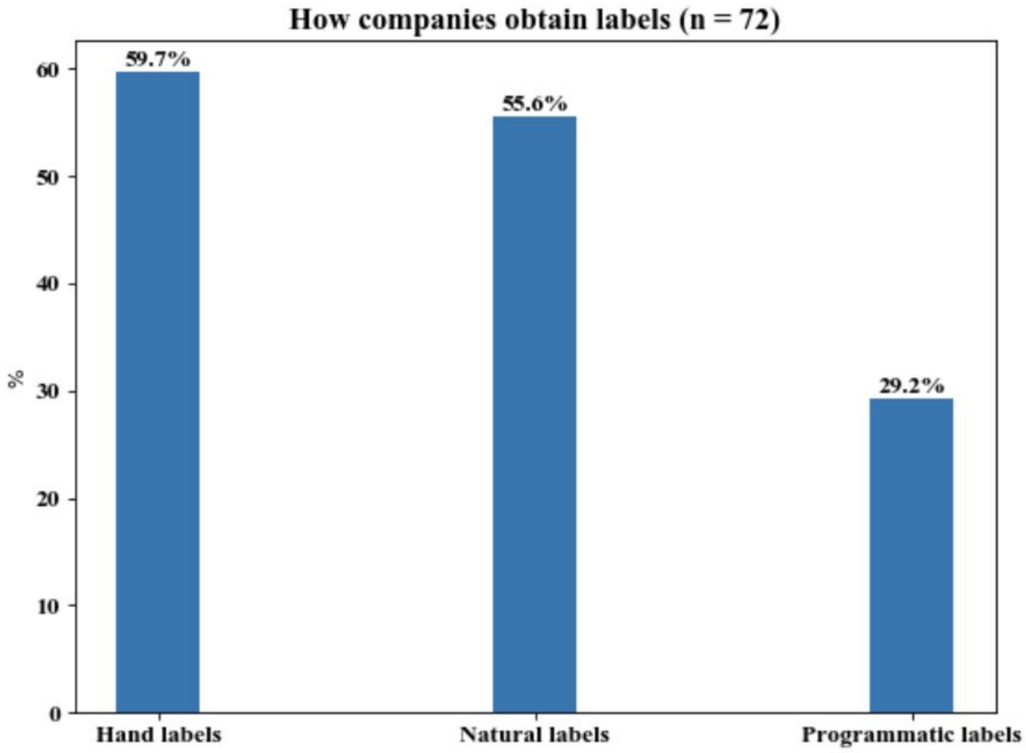
- The model's predictions can be automatically evaluated or partially evaluated by the system.
- Examples:
  - ETA
  - Ride demand prediction
  - Stock price prediction
  - Ads CTR
  - Recommender system

Natural labels

- You can engineer a task to have natural labels



Natural labels: surprisingly common

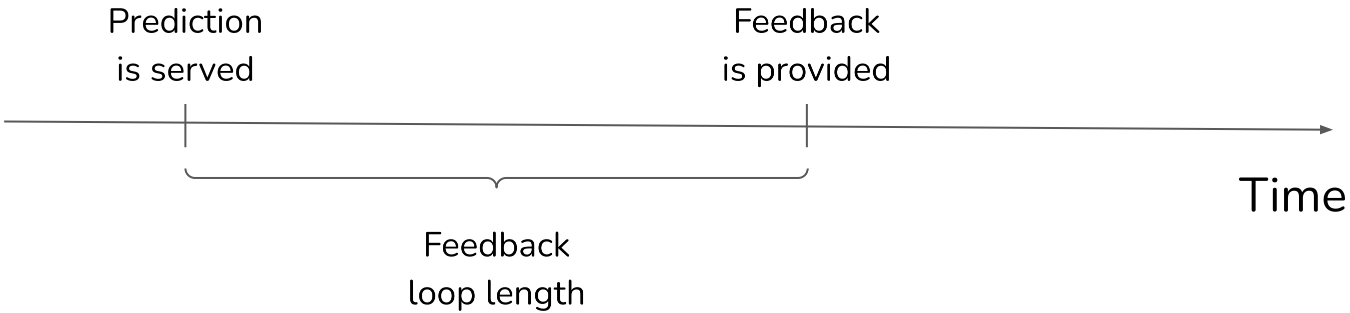


⚠️ Biases ⚠️

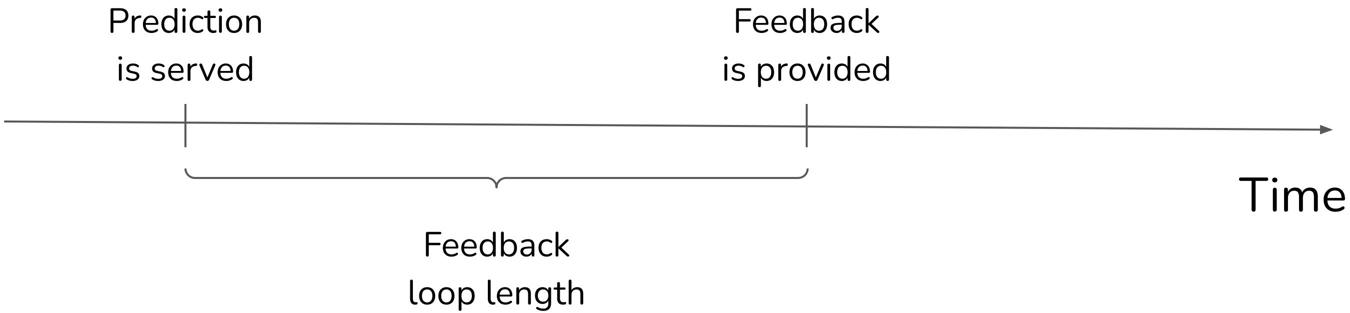
- Small sample size
- Companies might only use ML for tasks with natural labels

Claypot AI's real-time ML survey (2022)

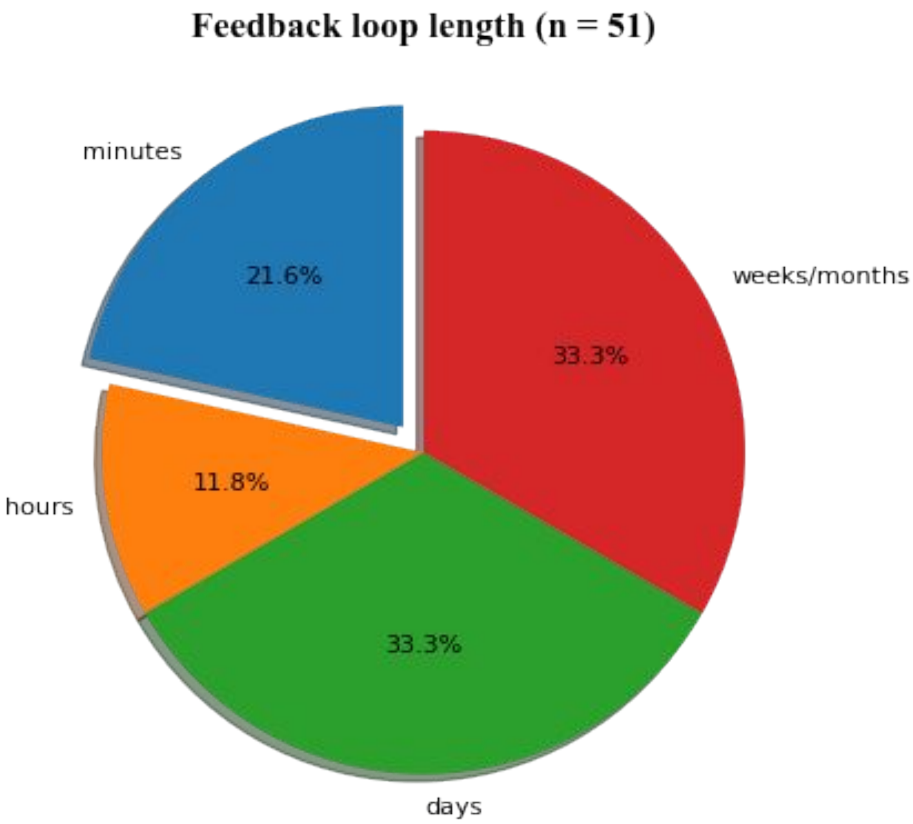
Delayed labels



Delayed labels



- Short feedback loop: minutes -> hours
    - Reddit / Twitter / TikTok's recommender systems
- Long feedback loop: weeks -> months
    - Stitch Fix's recommender systems
    - Fraud detection



Claypot AI's real-time ML survey (2022)

⚠️ Labels are often assumed ⚠️

- Recommendation:
  - Click -> good rec
  - After X minutes, no click -> bad rec

Too short

False negatives

Too long

Slow feedback

Speed vs. accuracy tradeoff

⚠️ Labels are often assumed ⚠️

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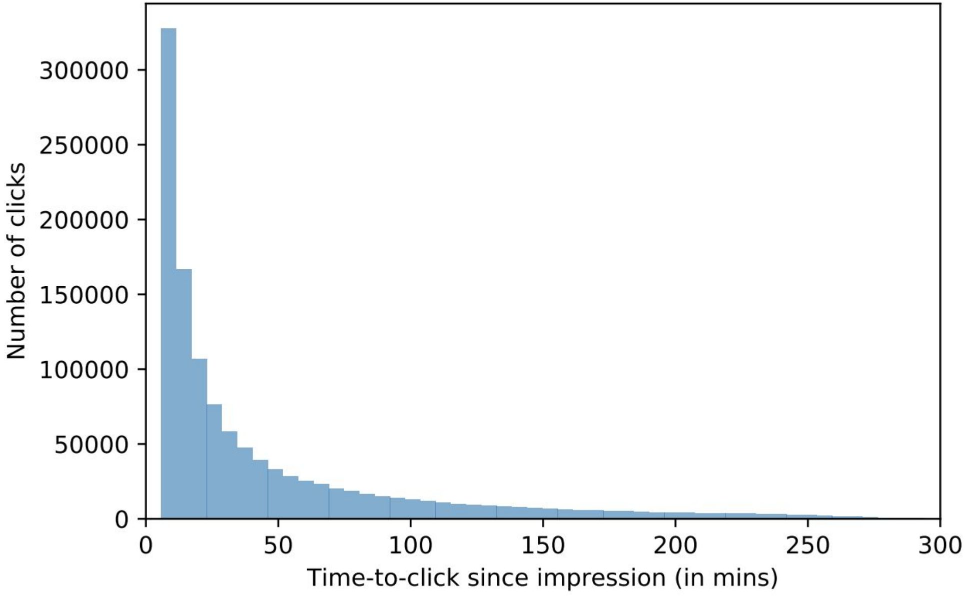
Too short

Too long

False negatives

Slow feedback



[Addressing Delayed Feedback for Continuous Training with Neural Networks in CTR prediction](#) (Ktena et al., 2019)

Causes of ML failures

Amazon scraps secret AI recruiting tool that showed bias against women

That is because Amazon's computer models were trained to vet applicants by observing patterns in resumes submitted to the company over a 10-year period. Most came from men, a reflection of male dominance across the tech industry.

In effect, Amazon's system taught itself that male candidates were preferable. It penalized resumes that included the word "women's," as in "women's chess club captain." And it downgraded graduates of two all-women's colleges, according to people familiar with the matter. They did not specify the names of the schools.

[Amazon scraps secret AI recruiting tool that showed bias against women](#) (Reuters, 2018)

Japan’s Henn na Hotel fires half its robot workforce

“Guests complained their robot room assistants thought snoring sounds were commands and would wake them up repeatedly during the night.”

https://www.hotelmanagement.net/tech/japan-s-henn-na-hotel-fires-half-its-robot-workforce

What is an ML failure?

A failure happens when one or more expectations of the system is violated.

Two types of expectations:

- Operational metrics: e.g. average latency, throughput, uptime
- ML metrics: e.g. accuracy, F1, BLEU score

What is an ML failure?

A failure happens when one or more expectations of the system is violated

- Traditional software: mostly operational metrics
- ML systems: operational + ML metrics
  - Ops: returns an English translation within 100ms latency on average
  - ML: BLEU score of 55 (out of 100)

ML system failures

- If you enter a sentence and get no translation back -> ops failure
- If one translation is incorrect -> ML failure?

ML system failures

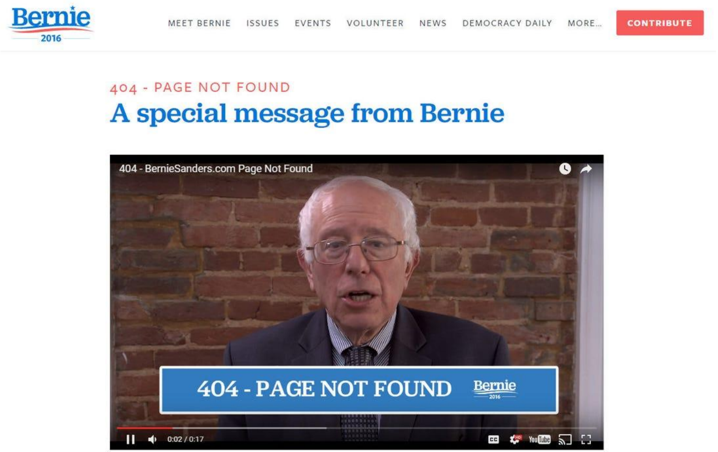
- If you enter a sentence and get no translation back -> ops failure
- If one translation is incorrect -> ML failure?

- Not necessarily: expected BLEU score < 100
- ML failure if translations are consistently incorrect

Ops failures

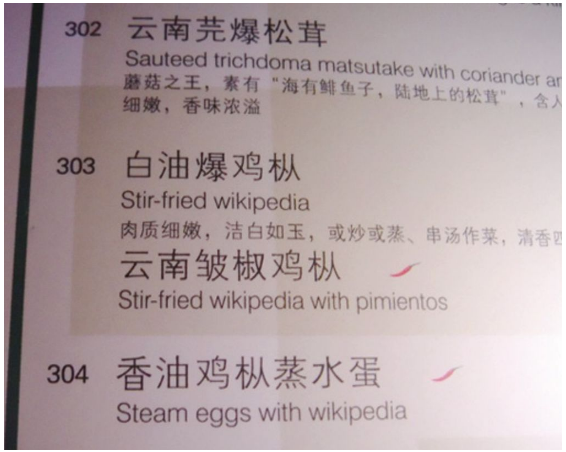
Visible

- 404, timeout, segfault, OOM, etc.



ML failures

Often invisible



Causes of ops failures (software system failures)

- Dependency failures
- Deployment failures
- Hardware failures
- Network failure: downtime / crash

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- Dependency failures
- Deployment failures
- Hardware failures
- Network failure: downtime / crash

60 / 96 ML systems failures are non-ML failures

(Papasian & Underwood, 2020)

As tooling & best practices around ML production mature,
there will be less surface for software failures

ML-specific failures (during/post deployment)

1. Production data differing from training data
2. Edge cases
3. Degenerate feedback loops

We've already covered problems
pre-deployment in previous lectures!

Production data differing from training data

- Train-serving skew:
  - Model performing well during development but poorly after production
- Data distribution shifts
  - Model performing well when first deployed, but poorly over time
  - ⚠️ What looks like data shifts might be caused by human errors ⚠️

Production data differing from training data

- Train-serving skew:
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- Data distribution shifts
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Common & crucial.
Will go into detail!

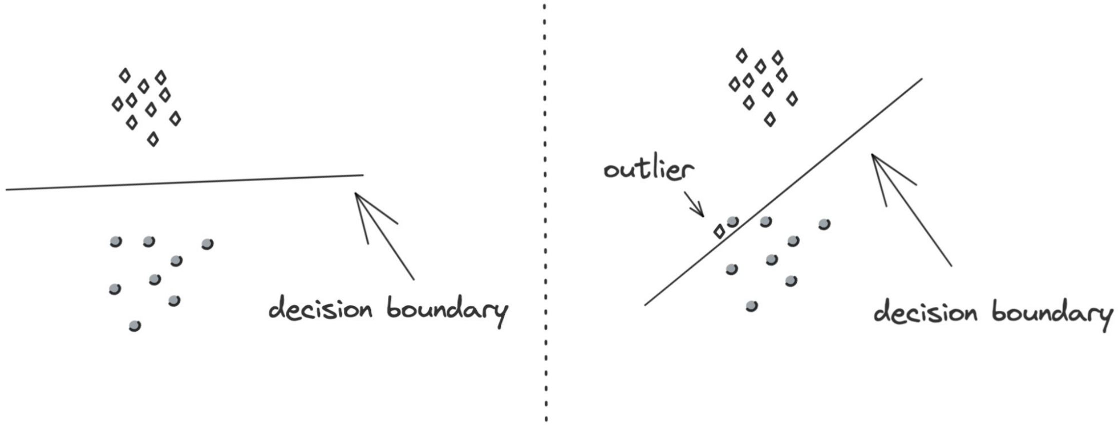
Edge cases

- Self-driving car (yearly)
  - Safely: 99.99%
  - Fatal accidents: 0.01%

Zoom poll: Would you use this car?

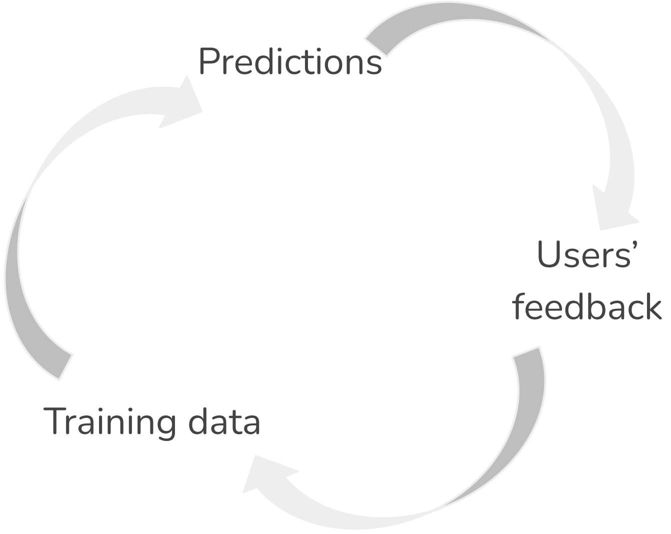
Edge case vs. outlier

- Outliers
  - Refer to inputs
  - Options to ignore/remove
- Edge cases
  - Refer to outputs
  - Can’t ignore/remove



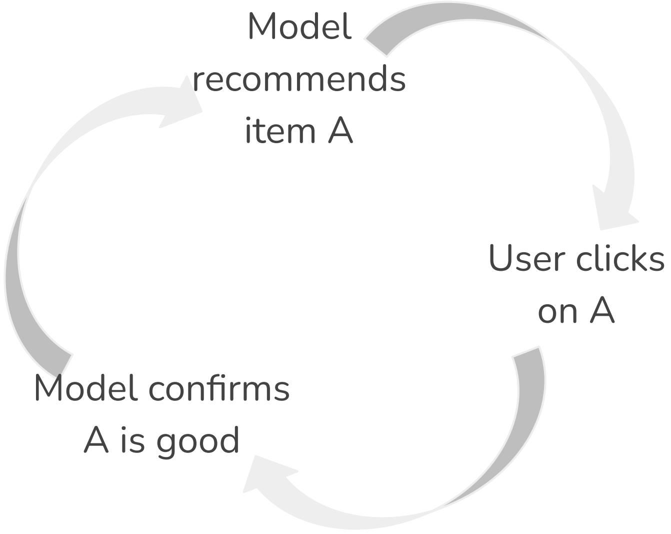
Degenerate feedback loops

- When predictions influence the feedback, which is then used to extract labels to train the next iteration of the model
- Common in tasks with natural labels



Degenerate feedback loops: recsys

- Originally, A is ranked marginally higher than B -> model recommends A
- After a while, A is ranked much higher than B



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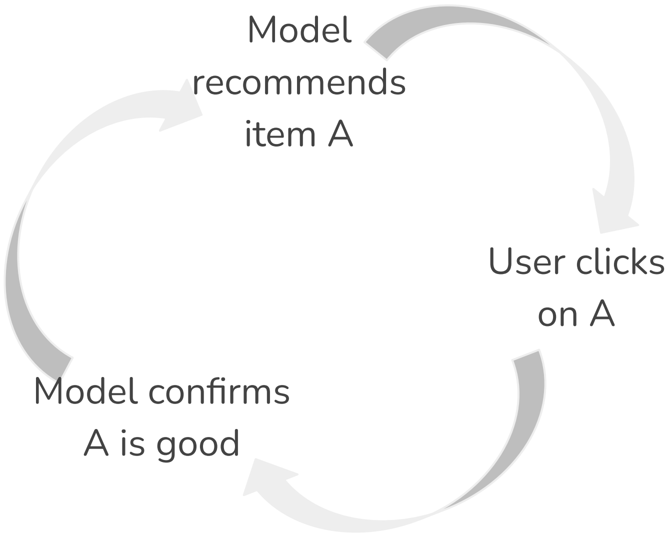

Over time, recommendations become more homogenous

Degenerate feedback loops: resume screening

- Originally, model thinks X is a good feature
- Model only picks resumes with X
- Hiring managers only see resumes with X, so only people with X are hired
- Model confirms that X is good

Replace X with:

- Has a name that is typically used for males
- Went to Stanford
- Worked at Google

Degenerate feedback loops: resume screening

- Originally, model thinks X is a good feature
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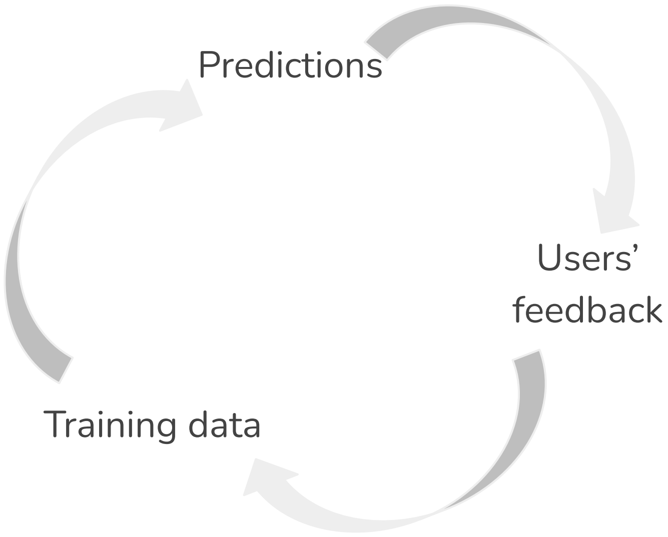
Tracking feature importance might help!

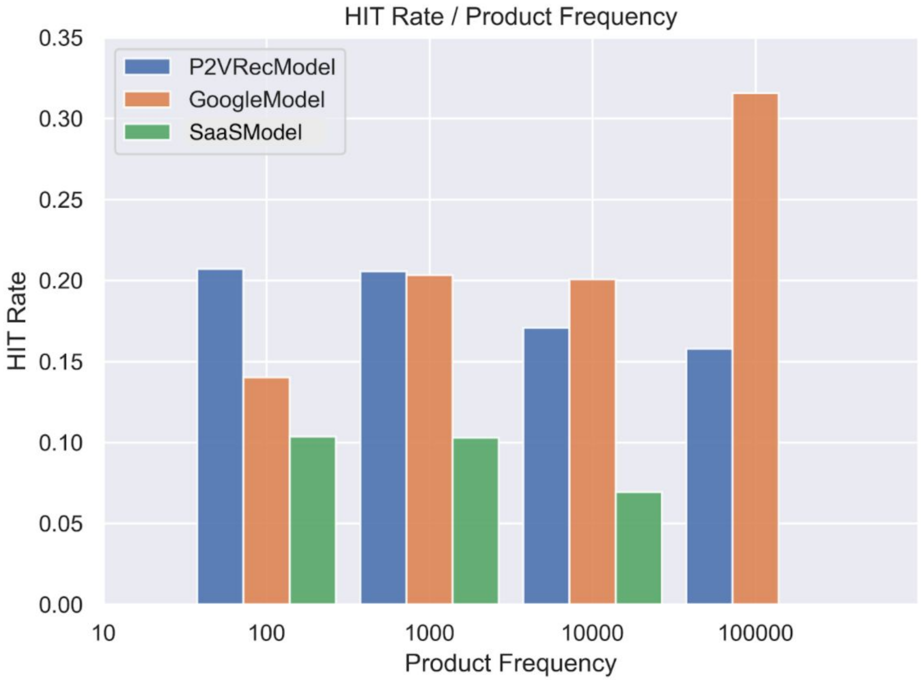
Detecting degenerate feedback loops

Only arise once models are in production -> hard to detect during training



Degenerate feedback loops: detect

- Average Rec Popularity (ARP)
  - Average popularity of the recommended items
- Average Percentage of Long Tail Items (APLT)
  - average % of long tail items being recommended
- Hit rate against popularity
  - Accuracy based on recommended items' popularity buckets



Beyond NDCG: behavioral testing of recommender systems with RecList (Chia et al., 2021)

Degenerate feedback loops: mitigate

1. Randomization
2. Positional features

Randomization

- Degenerate feedback loops increase output homogeneity
- Combat homogeneity by introducing randomness in predictions

Randomization

- Degenerate feedback loops increase output homogeneity
- Combat homogeneity by introducing randomness in predictions
- Recsys: show users random items & use feedback to determine items' quality

Positional features

- If a prediction’s position affects its feedback in any way, encode it.
    - Numerical: e.g. position 1, 2, 3, …
    - Boolean: e.g. shows first position or not

Positional features: naive

ID	Song	Genre	Year	Artist	User	1st Position	Click
1	Shallow	Pop	2020	Lady Gaga	listenr32	False	No
2	Good Vibe	Funk	2019	Funk Overlord	listenr32	False	No
3	Beat It	Rock	1989	Michael Jackson	fancypants	False	No
4	In Bloom	Rock	1991	Nirvana	fancypants	True	Yes
5	Shallow	Pop	2020	Lady Gaga	listenr32	True	Yes

Positional features: naive

ID	Song	Genre	Year	Artist	User	1st Position	Click
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Doesn't have this feature during inference?

Positional features: naive

ID	Song	Genre	Year	Artist	User	1st Position	Click
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Set to False during inference

Positional features: 2 models

1. Predicts the probability that the user will **see and consider** a recommendation given its position.
2. Predicts the probability that the user will **click on the item given that they saw and considered it**.

Model 2 doesn't use positional features

Breakout exercise

How might degenerate feedback loops occur? (10 mins)

1. Build a system to predict stock prices and use the predictions to make buy/sell decisions.
2. Use text scraped from the Internet to train a language model, then use the same language model to generate posts.

Discuss how you might mitigate the consequences of these feedback loops.

Data distribution shifts

- Source distribution: data the model is trained on
- Target distribution: data the model runs inference on

Supervised learning: $P(X, Y)$

1. $P(X, Y) = P(Y|X)P(X)$
2. $P(X, Y) = P(X|Y)P(Y)$

Types of data distribution shifts

Type	Meaning	Decomposition
Covariate shift	• P(X) changes • P(Y|X) remains the same	$P(X, Y) = P(Y\|X)P(X)$
Label shift	• P(Y) changes • P(X|Y) remains the same	$P(X, Y) = P(X\|Y)P(Y)$
Concept drift	• P(X) remains the same • P(Y|X) changes	$P(X, Y) = P(Y\|X)P(X)$

Covariate shift

- $P(X)$ changes
- $P(Y|X)$ remains the same

- Statistics: a covariate is an independent variable that can influence the outcome of a given statistical trial.
- Supervised ML: input features are covariates

Covariate shift

- P(X) changes
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- Statistics: a covariate is an independent variable that can influence the outcome of a given statistical trial.
- Supervised ML: input features are covariates
- Input distribution changes, but for *a given input*, output is the same

Covariate shift: example

- P(X) changes
- P(Y|X) remains the same

- Predicts P(cancer | patient)
- P(age > 40): training > production
- P(cancer | age > 40): training = production

Covariate shift: causes (training)

- P(X) changes
- P(Y|X) remains the same

- Predicts P(cancer | patient)
- P(age > 40):
  - training > production
- P(cancer | age > 40):
  - training = production

- Data collection
  - E.g. women >40 are encouraged by doctors to get checkups
  - Closely related to sampling biases
- Training techniques
  - E.g. oversampling of rare classes
- Learning process
  - E.g. active learning

Covariate shift: causes (prod)

- P(X) changes
- P(Y|X) remains the same

Changes in environments

- Ex 1: P(convert to paid user | free user)
  - New marketing campaign attracting users from with higher income
    - P(high income) increases
    - P(convert to paid user | high level) remains the same

Covariate shift: causes (prod)

- P(X) changes
- P(Y|X) remains the same

Changes in environments

- Ex 2: P(Covid | coughing sound)
  - Training data from clinics, production data from phone recordings
    - P(coughing sound) changes
    - P(Covid | coughing sound) remains the same

Covariate shift

- Research: if knowing in advance how the production data will differ from training data, use importance weighting
- Production: unlikely to know how a distribution will change in advance

Label shift

- $P(Y)$ changes
- $P(X|Y)$ remains the same

- Output distribution changes but for *a given output*, input distribution stays the same.

Label shift & covariate shift

- Predicts P(cancer | patient)
- P(age > 40): training > production
- P(cancer | age > 40): training = production
- P(cancer): training > production
- P(age > 40 | cancer): training = prediction

- P(X) changes
- P(Y|X) remains the same

- P(Y) changes
- P(X|Y) remains the same

P(X) change often leads to P(Y) change, so covariate shift often means label shift

Label shift & covariate shift

- Predicts P(cancer | patient)
- New preventive drug: reducing P(cancer | patient) for all patients
- P(age > 40): training > production
- P(cancer | age > 40): training > production
- P(cancer): training > production
- P(age > 40 | cancer): training = prediction

- P(X) changes
- ~~P(Y|X) remains the same~~

- P(Y) changes
- P(X|Y) remains the same

Not all label shifts are covariate shifts!

Concept Drift

- P(X) remains the same
- P(Y|X) changes

- Same input, expecting different output
- P(houses in SF) remains the same
- Covid causes people to leave SF, housing prices drop
    - P($5M | houses in SF)
        - Pre-covid: high
        - During-covid: low

Concept Drift

- P(X) remains the same
- P(Y|X) changes

- Concept drifts can be cyclic & seasonal
  - Ride sharing demands high during rush hours, low otherwise
  - Flight ticket prices high during holidays, low otherwise

General data changes

- Feature change
  - A feature is added/removed/updated

General data changes

- Feature change
  - A feature is added/removed/updated
- Label schema change
  - Original: *{“POSITIVE”: 0, “NEGATIVE”: 1}*
  - New: *{“POSITIVE”: 0, “NEGATIVE”: 1, “NEUTRAL”: 2}*

Detecting data distribution shifts

How to determine that two distributions are different?

Detecting data distribution shifts

How to determine that two distributions are different?

1. Compare statistics: mean, median, variance, quantiles, skewness, kurtosis, …
    - Compute mean & variance of a feature during training and compare them to the same values computed in production

Detecting data distribution shifts

How to determine that two distributions are different?

1. Compare statistics: mean, median, variance, quantiles, skewness, kurtosis, …
   - Not universal: only useful for distributions where these statistics are meaningful

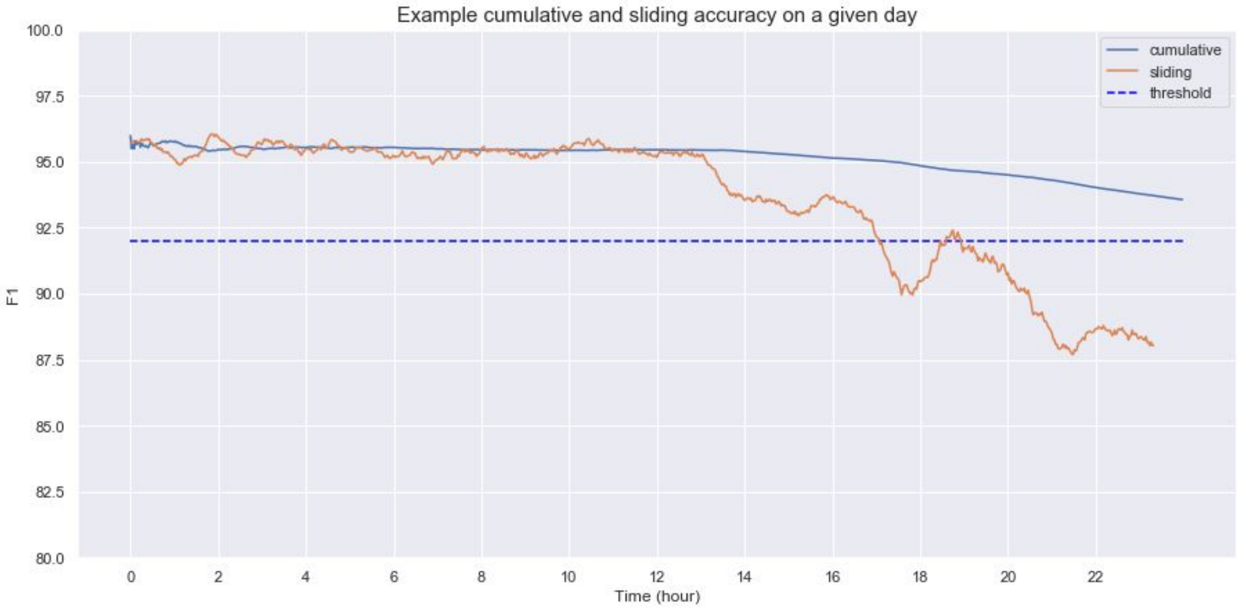
Detecting data distribution shifts

How to determine that two distributions are different?

1. Compare statistics: mean, median, variance, quantiles, skewness, kurtosis, …
    - Not universal: only useful for distributions where these statistics are meaningful
    - Inconclusive: if statistics differ, distributions differ. If statistics are the same, distributions can still differ.

Cumulative vs. sliding metrics

- Sliding: reset at each new time window



This image is based on an example from MadeWithML (Goku Mohandas).

Detecting data distribution shifts

How to determine that two distributions are different?

1. Compare statistics: mean, median, variance, quantiles, skewness, kurtosis, ...
2. Two-sample hypothesis test
    - Determine whether the difference between two populations is statistically significant
    - If yes, likely from two distinct distributions

E.g.
1. Data from yesterday
2. Data from today

Two-sample test: KS test (Kolmogorov–Smirnov)

- Pros
  - Doesn’t require any parameters of the underlying distribution
  - Doesn’t make assumptions about distribution
- Cons
  - Only works with one-dimensional data

- Useful for prediction & label distributions
- Not so useful for features

Two-sample test

Drift Detection

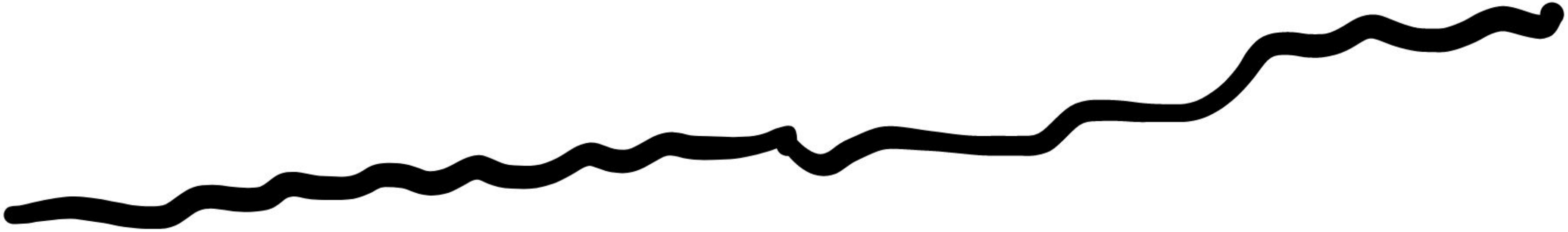
Detector	Tabular	Image	Time Series	Text	Categorical Features	Online	Feature Level
Kolmogorov-Smirnov	✓	✓		✓	✓		✓
Maximum Mean Discrepancy	✓	✓		✓	✓	✓	
Learned Kernel MMD	✓	✓		✓	✓		
Least-Squares Density Difference	✓	✓		✓	✓	✓	
Chi-Squared	✓				✓		✓
Mixed-type tabular data	✓				✓		✓
Classifier	✓	✓	✓	✓	✓		
Spot-the-diff	✓	✓	✓	✓	✓		✓
Classifier Uncertainty	✓	✓	✓	✓	✓		
Regressor Uncertainty	✓	✓	✓	✓	✓		

alibi-detect (OS)

Most tests work better on low-dim data, so dim reduction is recommended beforehand!

Not all shifts are equal

- Sudden shifts vs. gradual shifts
  - Sudden shifts are easier to detect than gradual shifts



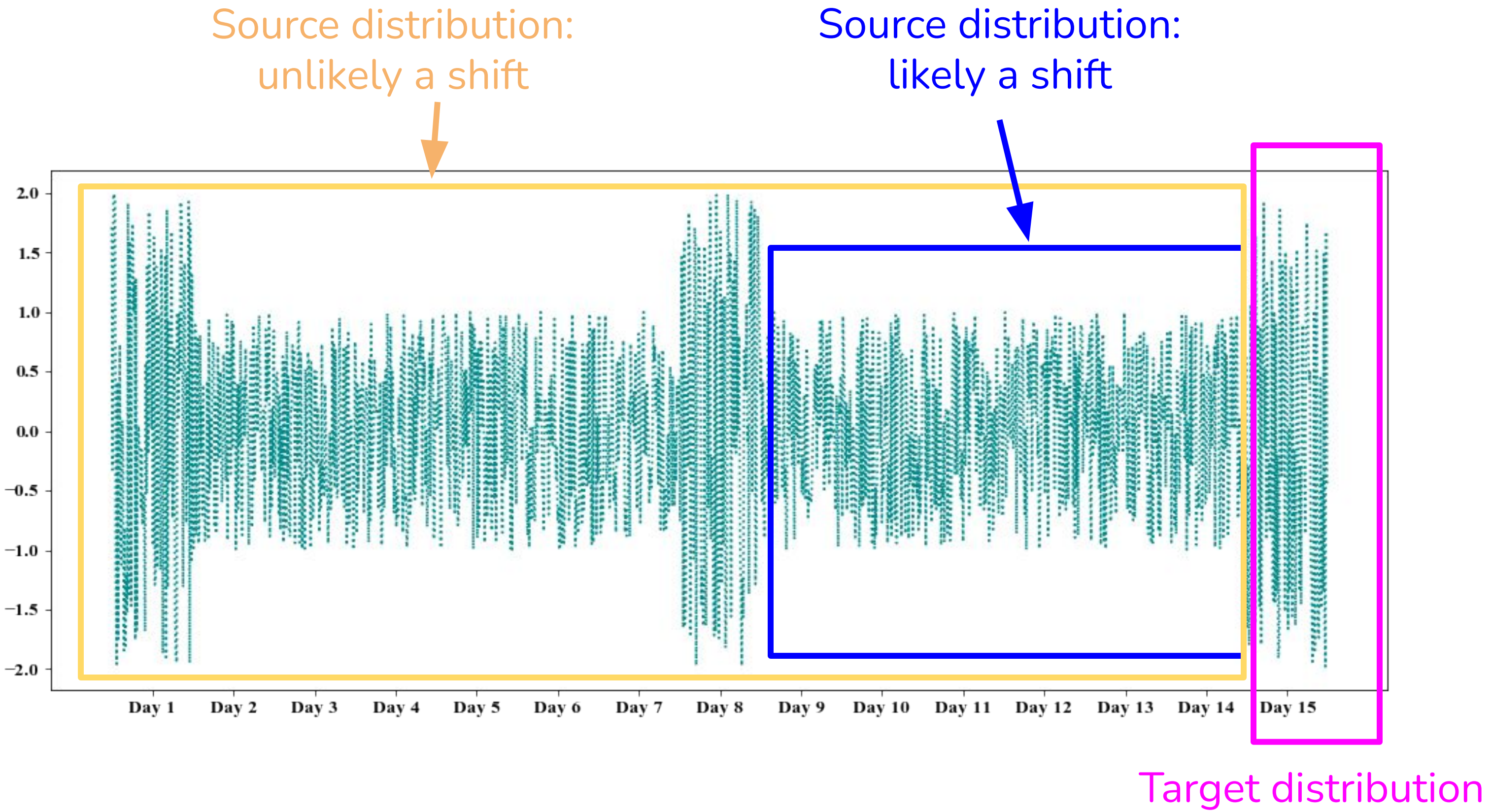
Not all shifts are equal

- Sudden shifts vs. gradual shifts
- Spatial shifts vs. temporal shifts

- New device (e.g. mobile vs. desktop)
- New users (e.g. new country)

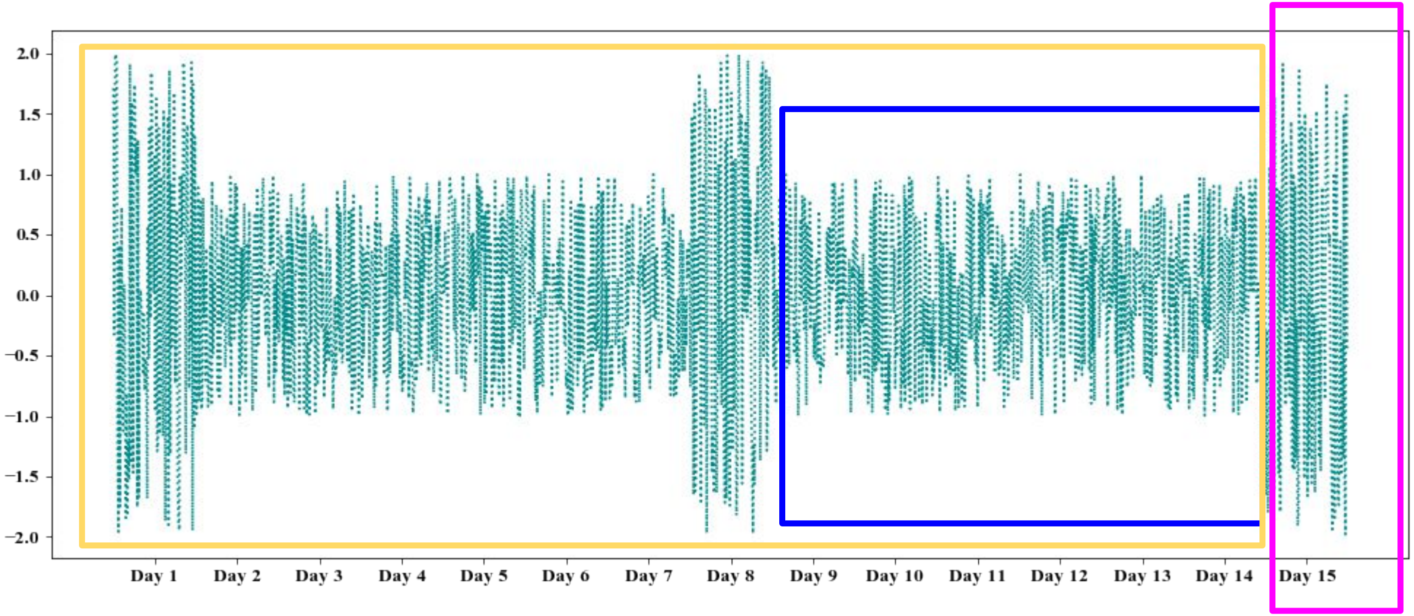
E.g. same users, same device, but behaviors change over time

Temporal shifts: time window scale matters



Temporal shifts: time window scale matters

Difficulty is compounded
by seasonal variation



Temporal shifts: time window scale matters

- Too short window: false alarms of shifts
- Too long window: takes long to detect shifts

    - Granularity level: hourly, daily

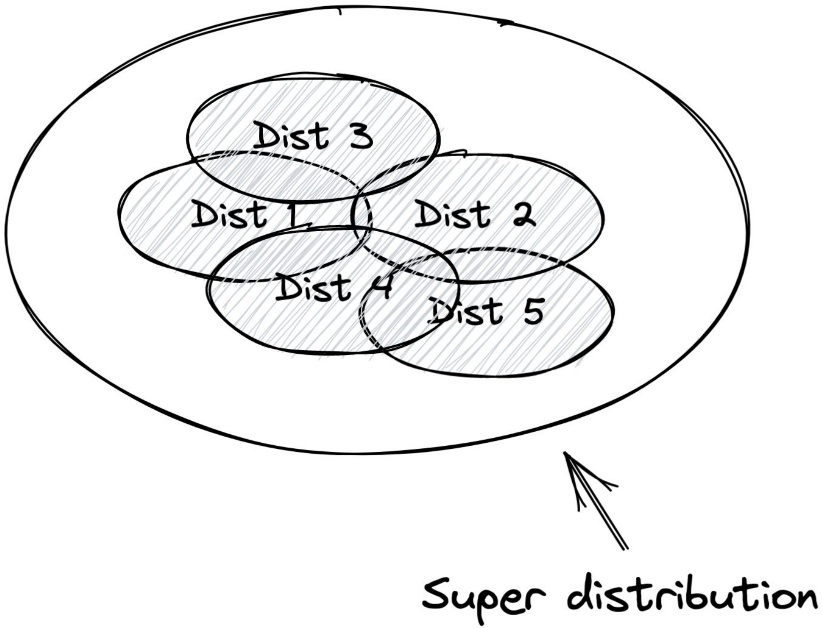
Temporal shifts: time window scale matters

- Too short window: false alarms of shifts
- Too long window: takes long to detect shifts

- Granularity level: hourly, daily
- Merge shorter time scale windows -> larger time scale window
- RCA: automatically analyze various window sizes

Addressing data distribution shifts

1. Train model using a massive dataset



Addressing data distribution shifts

1. Train model using a massive dataset
2. Retrain model with new data from new distribution
    - Mode
        - Train from scratch
        - Fine-tune

Addressing data distribution shifts

1. Train model using a massive dataset
2. Retrain model with new data from new distribution
    - Mode
    - Data
        - Use data from when data started to shift
        - Use data from the last X days/weeks/months
        - Use data form the last fine-tuning point

Need to figure out not just when to retrain models, but also how and what data

Monitoring & Observability

Monitoring vs. observability

- Monitoring: tracking, measuring, and logging different metrics that can help us determine when something goes wrong
- Observability: setting up our system in a way that gives us visibility into our system to investigate what went wrong

Monitoring vs. observability

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Instrumentation

- adding timers to your functions
- counting NaNs in your features
- logging unusual events e.g. very long inputs
- ...

Monitoring vs. observability

- Monitoring: tracking, measuring, and logging different metrics that can help us determine when something goes wrong
- Observability: setting up our system in a way that gives us visibility into our system to investigate what went wrong

Observability is part of monitoring

Monitoring is all about metrics

- Operational metrics
- ML-specific metrics

Operational metrics

- Latency
- Throughput
- Requests / minute/hour/day
- % requests that return with a 2XX code
- CPU/GPU utilization
- Memory utilization
- **Availability**
- etc.

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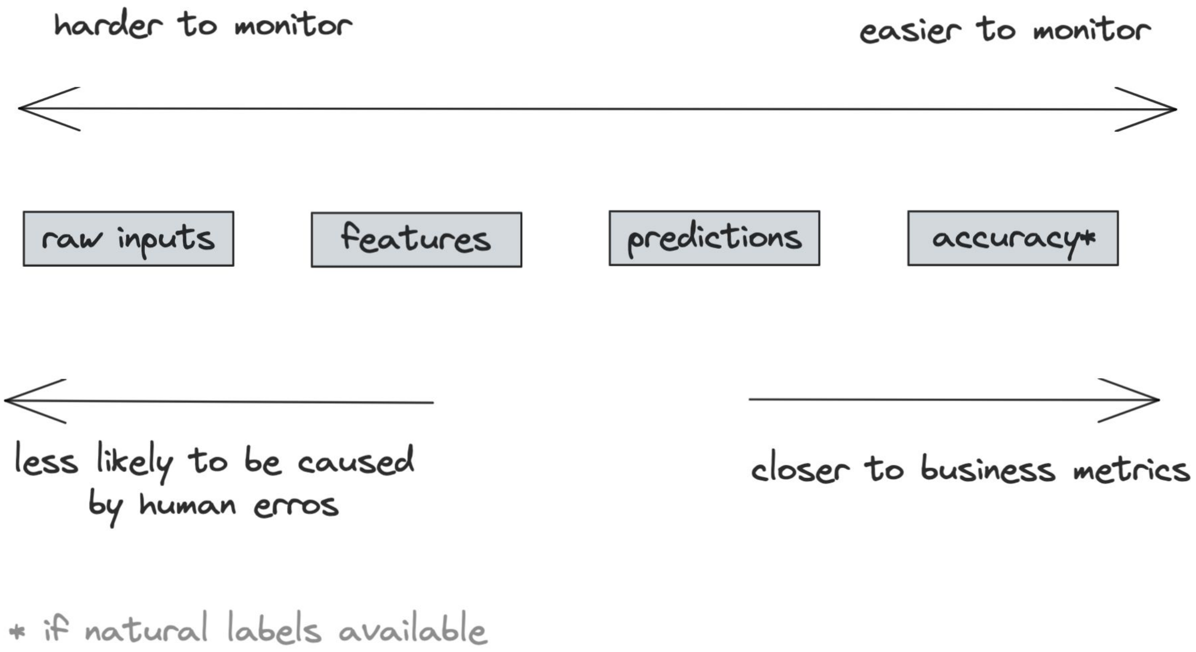
SLA example

- Up means:
  - median latency <200ms
  - 99th percentile <2s
- 99.99% uptime (four-nines)

SLA for ML?

ML metrics: what to monitor



Monitoring #1: accuracy-related metrics

- Most direct way to monitor a model's performance
  - Can only do as fast as when feedback is available

Monitoring #1: accuracy-related metrics

- Most direct way to monitor a model's performance
- Collect as much feedback as possible
- Example: YouTube video recommendations
    - Click through rate
    - Duration watched
    - Completion rate
    - Take rate

Monitoring #2: predictions

- Predictions are low-dim: easy to visualize, compute stats, and do two-sample tests
- Changes in prediction dist. generally mean changes in input dist.

Monitoring #2: predictions

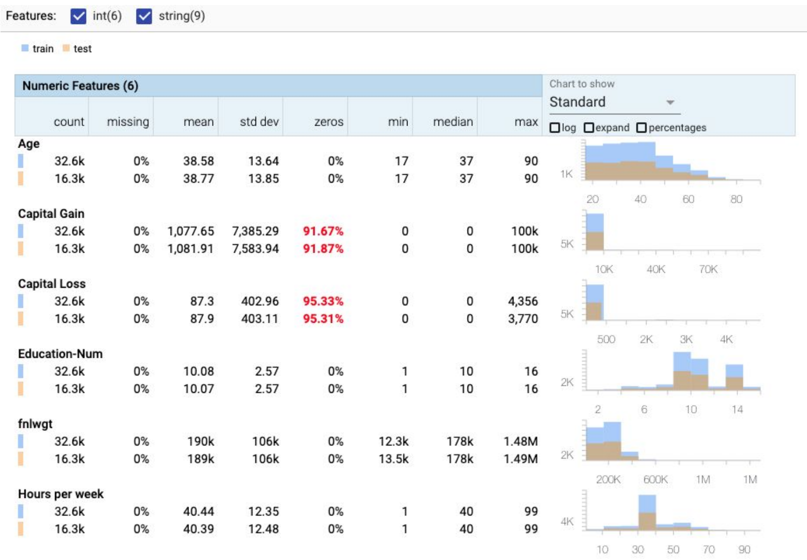
- Predictions are low-dim: easy to visualize, compute stats, and do two-sample tests
- Changes in prediction dist. generally mean changes in input dist.
- Monitor odd things in predictions
    - E.g. if predictions are all False in the last 10 mins

Monitoring #3: features

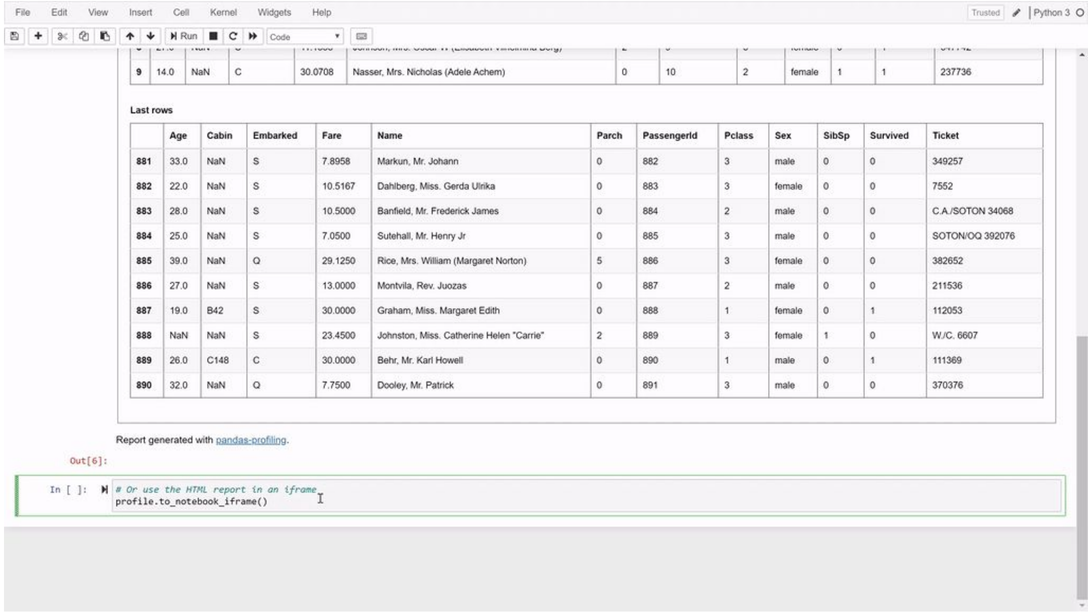
- Most monitoring tools focus on monitoring features
- Feature schema expectations
  - Generated from the source distribution
  - If violated in production, possibly something is wrong
- Example expectations
  - Common sense: e.g. “the” is most common word in English
  - min, max, or median values of a feature are in [a, b]
  - All values of a feature satisfy a regex
  - Categorical data belongs to a predefined set
  - FEATURE_1 > FEATURE_B

Generate expectations with profiling & visualization

- Examining data & collecting:
  - statistics
  - informative summaries
- [pandas-profiling](#)
- [facets](#)



	count	missing	mean	std dev	zeros	min	median	max
Age	32.6k	0%	38.58	13.64	0%	17	37	90
	16.3k	0%	38.77	13.85	0%	17	37	90
Capital Gain	32.6k	0%	1,077.65	7,385.29	91.67%	0	0	100k
	16.3k	0%	1,081.91	7,583.94	91.87%	0	0	100k
Capital Loss	32.6k	0%	87.3	402.96	95.33%	0	0	4,356
	16.3k	0%	87.9	403.11	95.31%	0	0	3,770
Education-Num	32.6k	0%	10.08	2.57	0%	1	10	16
	16.3k	0%	10.07	2.57	0%	1	10	16
fnlwgt	32.6k	0%	190k	106k	0%	12.3k	178k	1.48M
	16.3k	0%	189k	106k	0%	13.5k	178k	1.49M
Hours per week	32.6k	0%	40.44	12.35	0%	1	40	99
	16.3k	0%	40.39	12.48	0%	1	40	99



9	14.0	NaN	C	30.0708	Nasser, Mrs. Nicholas (Adele Achem)	0	10	2	female	1	1	237736

	Age	Cabin	Embarked	Fare	Name	Parch	PassengerId	Pclass	Sex	SibSp	Survived	Ticket
881	33.0	NaN	S	7.8958	Markun, Mr. Johann	0	882	3	male	0	0	349257
882	22.0	NaN	S	10.5167	Dahlberg, Miss. Gerda Ulrika	0	883	3	female	0	0	7552
883	28.0	NaN	S	10.5000	Banfield, Mr. Frederick James	0	884	2	male	0	0	C.A./SOTON 34068
884	25.0	NaN	S	7.0500	Sutehall, Mr. Henry Jr	0	885	3	male	0	0	SOTON/OQ 392076
885	39.0	NaN	Q	29.1250	Rice, Mrs. William (Margaret Norton)	5	886	3	female	0	0	382652
886	27.0	NaN	S	13.0000	Montvila, Rev. Juozas	0	887	2	male	0	0	211536
887	19.0	B42	S	30.0000	Graham, Miss. Margaret Edith	0	888	1	female	0	1	112053
888	NaN	NaN	S	23.4500	Johnston, Miss. Catherine Helen "Carrie"	2	889	3	female	1	0	W./C. 6607
889	26.0	C148	C	30.0000	Behr, Mr. Karl Howell	0	890	1	male	0	1	111369
890	32.0	NaN	Q	7.7500	Dooley, Mr. Patrick	0	891	3	male	0	0	370376

```
# Or use the HTML report in an iframe
profile.to_notebook_iframe()
```

Monitoring #3: features

- Feature schema expectations

Table shape

- `expect_column_to_exist`
- `expect_table_columns_to_match_ordered_list`
- `expect_table_columns_to_match_set`
- `expect_table_row_count_to_be_between`
- `expect_table_row_count_to_equal`
- `expect_table_row_count_to_equal_other_table`

Missing values, unique values, and types

- `expect_column_values_to_be_unique`
- `expect_column_values_to_not_be_null`
- `expect_column_values_to_be_null`
- `expect_column_values_to_be_of_type`
- `expect_column_values_to_be_in_type_list`

```
expect_column_values_to_be_between(
    column="room_temp",
    min_value=60,
    max_value=75,
    mostly=.95
)
```

"Values in this column should be between 60 and 75, at least 95% of the time."

"Warning: more than 5% of values fell outside the specified range of 60 to 75."

[GitHub - great-expectations/great_expectations]

Monitoring #3: features schema with pydantic

```python
from pydantic import BaseModel, ValidationError, validator


class UserModel(BaseModel):
    name: str
    username: str
    password1: str
    password2: str

    @validator('name')
    def name_must_contain_space(cls, v):
        if ' ' not in v:
            raise ValueError('must contain a space')
        return v.title()

    @validator('password2')
    def passwords_match(cls, v, values, **kwargs):
        if 'password1' in values and v != values['password1']:
            raise ValueError('passwords do not match')
        return v

    @validator('username')
    def username_alphanumeric(cls, v):
        assert v.isalnum(), 'must be alphanumeric'
        return v
```

```python
user = UserModel(
    name='samuel colvin',
    username='scolvin',
    password1='zxcvbn',
    password2='zxcvbn',
)
print(user)
#> name='Samuel Colvin' username='scolvin' password1='zxcvbn' password2='zxcvbn'

try:
    UserModel(
        name='samuel',
        username='scolvin',
        password1='zxcvbn',
        password2='zxcvbn2',
    )
except ValidationError as e:
    print(e)
    """
    2 validation errors for UserModel
    name
      must contain a space (type=value_error)
    password2
      passwords do not match (type=value_error)
    """
```

https://pydantic-docs.helpmanual.io/usage/validators/

Monitoring #3: features schema with TFX

```
# Generate training stats & schema
train_stats = tfdv.generate_statistics_from_dataframe(df)
schema = tfdv.infer_schema(statistics=train_stats)
```

```
schema
```

```
feature {
  name: "1"
  type: FLOAT
  presence {
    min_fraction: 1.0
    min_count: 1
  }
  shape {
    dim {
      size: 1
    }
  }
}
```

```
# Generate serving stats
serving_stats = tfdv.generate_statistics_from_dataframe(serving_df)
# Domain knowledge required
tfdv.get_feature(schema, "diabetesMed").skew_comparator.infinity_norm.threshold = 0.03
# Compare serving stats to training stats to detect skew
skew_anomalies = tfdv.validate_statistics(
    statistics=train_stats,
    schema=schema,
    serving_statistics=serving_stats)
```

	Anomaly short description	Anomaly long description
Feature name		
'payer_code'	High Linfty distance between current and previous	The Linfty distance between current and previous is 0.0342144 (up to six significant digits), above the threshold 0.03. The feature value with maximum difference is: MC
'diabetesMed'	High Linfty distance between training and serving	The Linfty distance between training and serving is 0.0325464 (up to six significant digits), above the threshold 0.03. The feature value with maximum difference is: No

How To Evaluate MLOps Tools (Hamel Husain, CS 329S Lecture 9, 2022)

Feature monitoring problems

1. Compute & memory cost
    a. 100s models, each with 100s features
    b. Computing stats for 10000s of features is costly

Feature monitoring problems

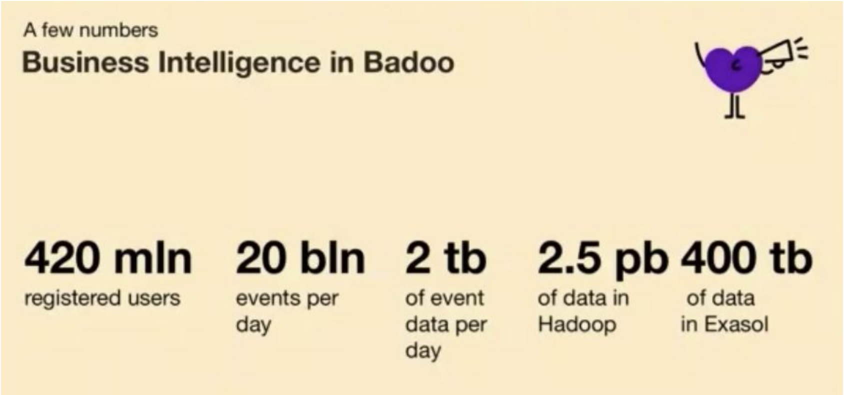
1. Compute & memory cost
2. Alert fatigue
    a. Most expectation violations are benign

Feature monitoring problems

1. Compute & memory cost
2. Alert fatigue
3. Schema management
    a. Feature schema changes over time
    b. Need to find a way to map feature to schema version

Monitoring toolbox: logs

- Log everything
- A stream processing problem



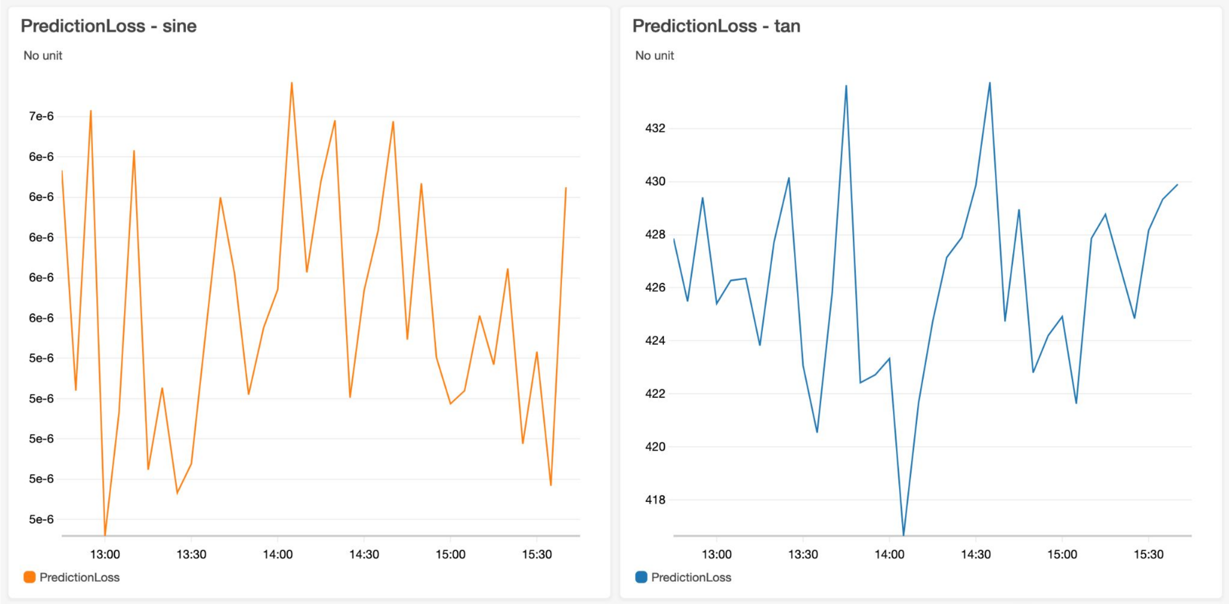
Vladimir Kazanov ([Badoo 2019])

"If it moves, we track it. Sometimes we'll draw a graph of something that isn't moving yet, just in case it decides to make a run for it."

Ian Malpass ([Etsy 2011])

Monitoring toolbox: dashboards

- Make monitoring accessible to non-engineering stakeholders
- Good for visualizations but insufficient for discovering distribution shifts



Monitoring toolbox: alerts

- 3 components
  - Alert policy: condition for alert
  - Notification channels
  - Description
- Alert fatigue
  - How to send only meaningful alerts?

```
## Recommender model accuracy below 90%

${timestamp}: This alert originated from the service ${service-name}
```

Monitoring -> Continual Learning

- Monitoring is passive
  - Wait for a shift to happen to detect it
- Continual learning is active
  - Update your models to address shifts

Machine Learning Systems Design

Next class:

- Continual Learning
- Data Distribution Shifts on Streams
  with Shreya Shankar

Stanford University