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# C1W3 Slides

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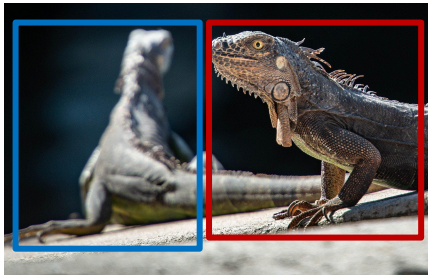
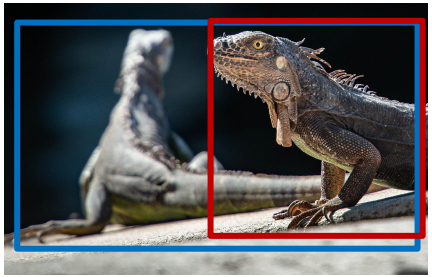
# Define data and establish baseline

## Why is data definition hard?

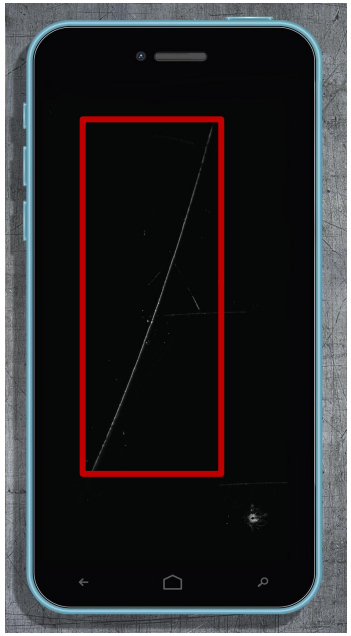
# Iguana detection example

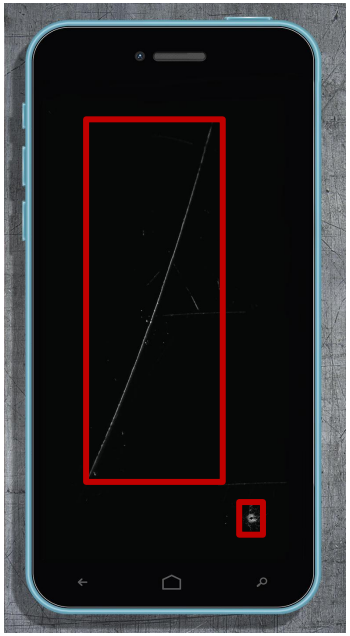




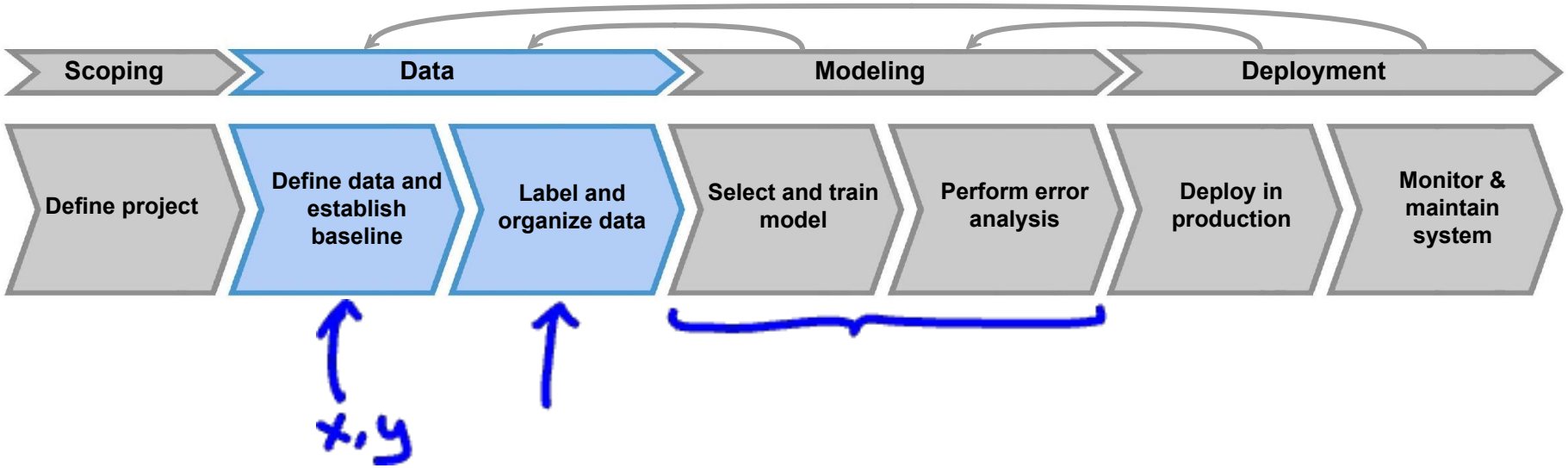
Labeling instructions: "Use bounding boxes to indicate the position of iguanas"

# Phone defect detection





# Data stage


Scoping
Data
Modeling
Deployment
Define project
Define data and establish baseline
Label and organize data
Select and train model
Perform error analysis
Deploy in production
Monitor & maintain system
x, y

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# Define data and establish baseline

## More label ambiguity examples

# Speech recognition example

"Um, nearest gas station"

"Umm, nearest gas station"

”Nearest gas station [unintelligible]"

# User ID merge example

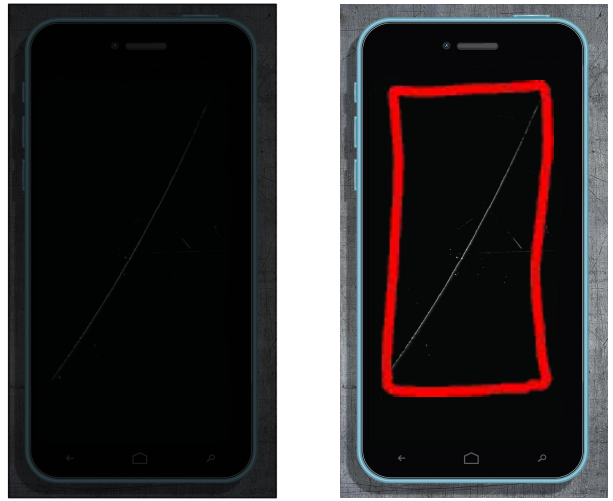
| | Job Board (website) |
|---|---|
| Email | nova@deeplearning.ai |
| First Name | Nova |
| Last Name | Ng |
| Address | 1234 Jane Way |
| State | CA |
| Zip | 94304 |

- is it a bot/spam account?
- fraudulent transaction?
- looking for job?

1 if same

0 if different

# Data definition questions



- What is the input $x$?
  - Lightning? Contrast? Resolution?
  - What features need to be included?
- What is the target label $y$?
  - How can we ensure labelers give consistent labels?

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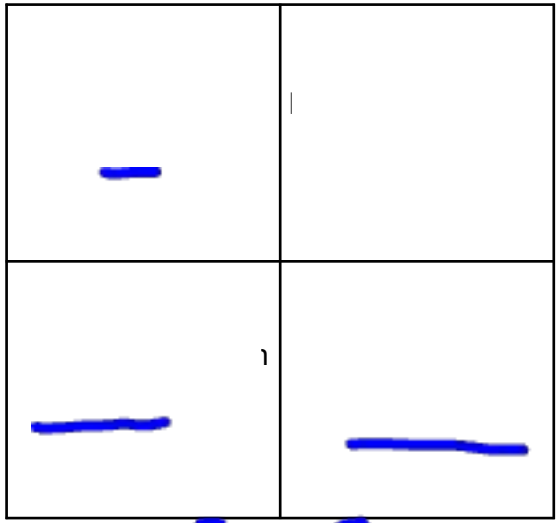
# Define data and establish baseline

## Major types of data problems

# Major types of data problems




≤ 10,000

Clean labels are critical.

> 10,000

Emphasis on data process.

Humans can label data.

Data augmentation.

Harder to obtain more data.

# Unstructured vs. structured data

Unstructured data

- May or may not have huge collection of unlabeled examples $x$.
- Humans can label more data.
- Data augmentation more likely to be helpful.

Structured data

- May be more difficult to obtain more data.
- Human labeling may not be possible (with some exceptions).

# Small data vs. big data

< 10,000 > 10,000

Small data

- Clean labels are critical.
- Can manually look through dataset and fix labels.
- Can get all the labelers to talk to each other.

Big data

- Emphasis data process.

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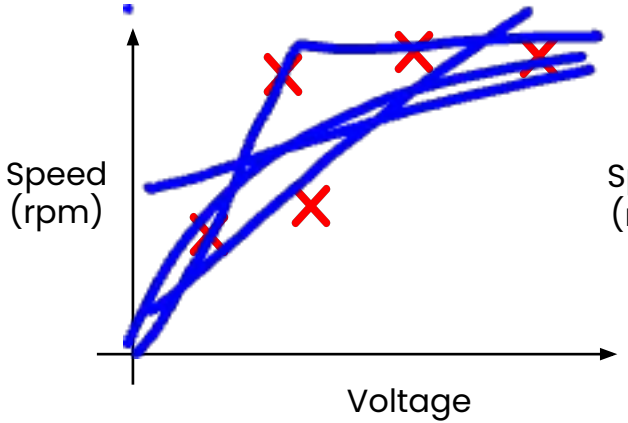
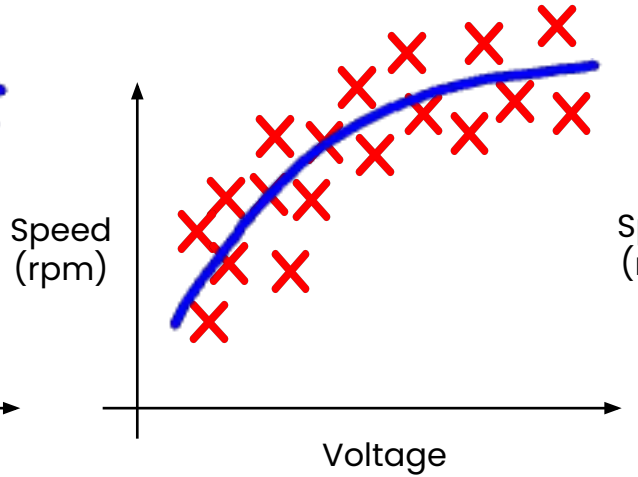
# Define data and establish baseline

## Small data and label consistency

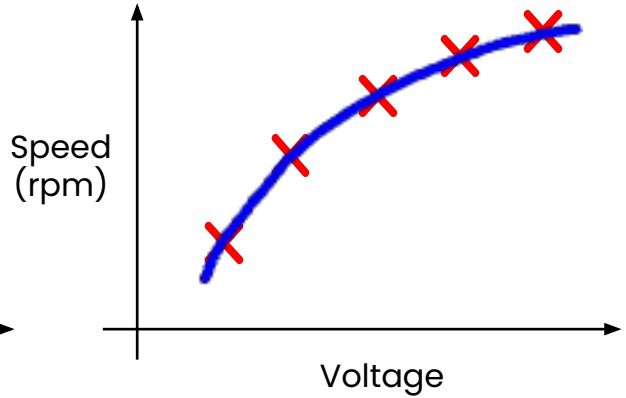
# Why label consistency is important




- Small data
- Noisy labels

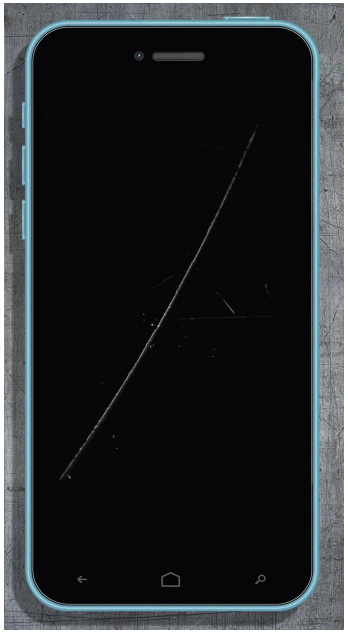


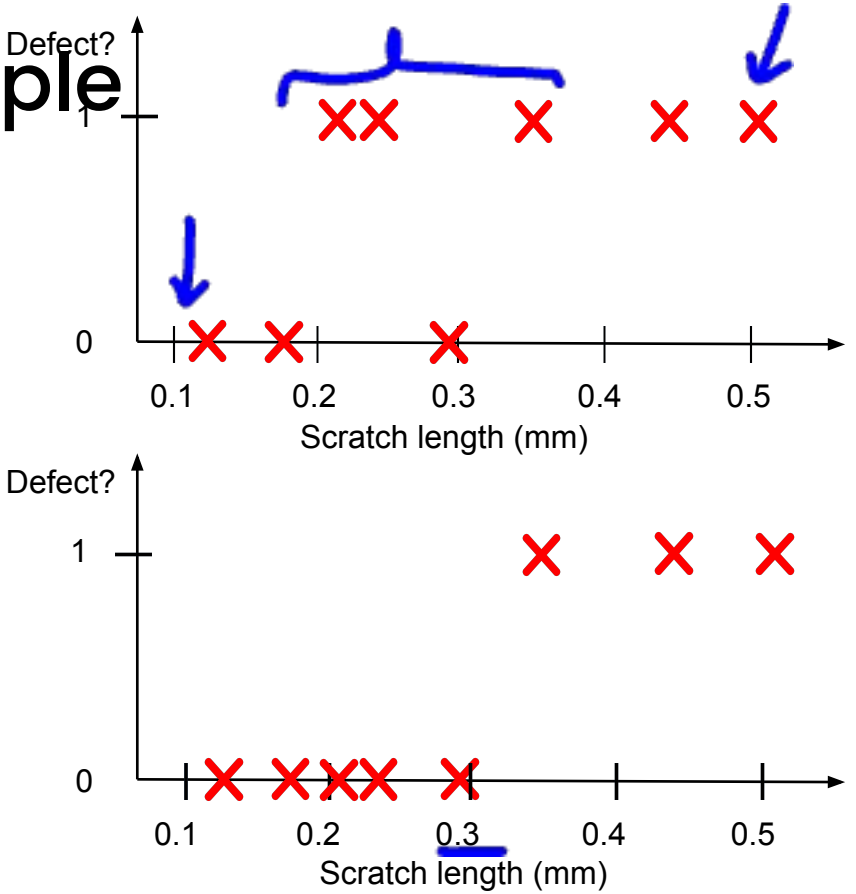

- Big data
- Noisy labels




- Small data
- Clean (consistent) labels

# Phone defect example





# Big data problems can have small data challenges too

Problems with a large dataset but where there's a long tail of rare events in the input will have small data challenges too.

- Web search
- Self-driving cars
- Product recommendation systems

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# Define data and establish baseline

## Improving label consistency

# Improving label consistency

- Have multiple labelers label same example.
- When there is disagreement, have MLE, subject matter expert (SME) and/or labelers discuss definition of $y$ to reach agreement.
- If labelers believe that $x$ doesn't contain enough information, consider changing $x$.
- Iterate until it is hard to significantly increase agreement.

# Examples

- Standardize labels

  "Um, nearest gas station"

  "Umm, nearest gas station"

  ”Nearest gas station [unintelligible]”

  → "Um, nearest gas station"

- Merge classes

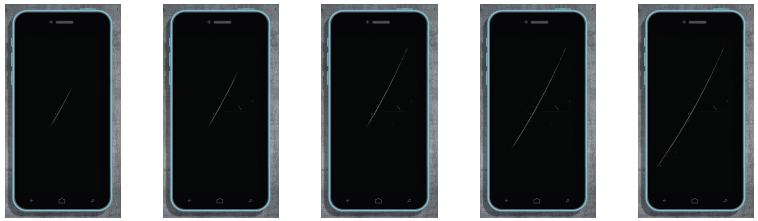
Deep scratch

Shallow scratch

→ Scratch

# Have a class/label to capture uncertainty

- Defect: 0 or 1



Alternative: 0,  Borderline, 1

- Unintelligible audio 

“nearest go”

“nearest grocery”

“nearest [unintelligible]”

# Small data vs. big data (unstructured data)

Small data

- Usually small number of labelers.
- Can ask labelers to discuss specific labels.

Big data

- Get to consistent definition with a small group.
- Then send labeling instructions to labelers.
- Can consider having multiple labelers label every example and using voting or consensus labels to increase accuracy.

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# Define data and establish baseline

## Human level performance (HLP)

# Why measure HLP?

- Estimate Bayes error / irreducible error to help with error analysis and prioritization.

99%

| Ground Truth Label | |
|---|---|
| 1 | ✓ |
| 1 | ✗ |
| 1 | ✓ |
| 0 | ✓ |
| 0 | ✓ |
| 0 | ✗ |

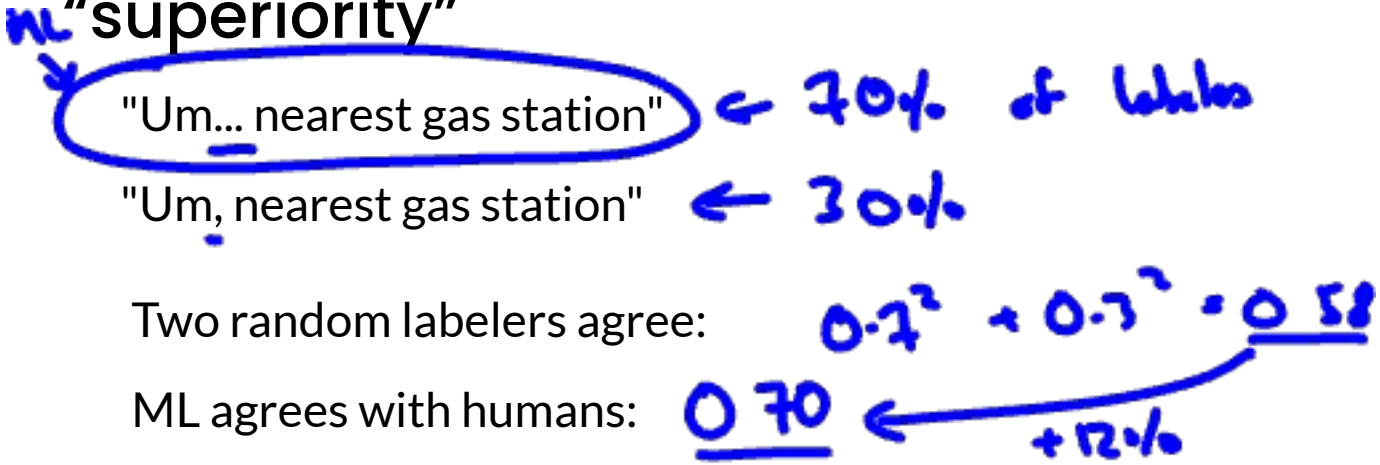
Human?

66.7% accuracy

# Other uses of HLP

- In academia, establish and beat a respectable benchmark to support publication.
- Business or product owner asks for 99% accuracy. HLP helps establish a more reasonable target.
- “Prove” the ML system is superior to humans doing the job and thus the business or product owner should adopt it.

# The problem with beating HLP as a “proof” of ML “superiority”




The 12% better performance is not important for anything! This can also mask more significant errors ML may be making.

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# Define data and establish baseline

## Raising HLP

# Raising HLP

When the ground truth label is externally defined, HLP gives an estimate for Bayes error / irreducible error.

But often ground truth is just another human label.

| Ground Truth Label | Inspector |
|---|---|
| 1 | 1 |
| 1 | 0 |
| 1 | 1 |
| 0 | 0 |
| 0 | 0 |
| 0 | 1 |

# Raising HLP

- When the label *y* comes from a human label, HLP << 100% may indicate ambiguous labeling instructions.

Um, Um...

- Improving label consistency will raise HLP.

- This makes it harder for ML to beat HLP. But the more consistent labels will raise ML performance, which is ultimately likely to benefit the actual application performance.

# HLP on structured data

Structured data problems are less likely to involve human labelers, thus HLP is less frequently used.

Some exceptions:

- User ID merging: Same person?
- Based on network traffic, is the computer hacked?
- Is the transaction fraudulent?
- Spam account? Bot?
- From GPS, what is the mode of transportation – on foot, bike, car, bus?

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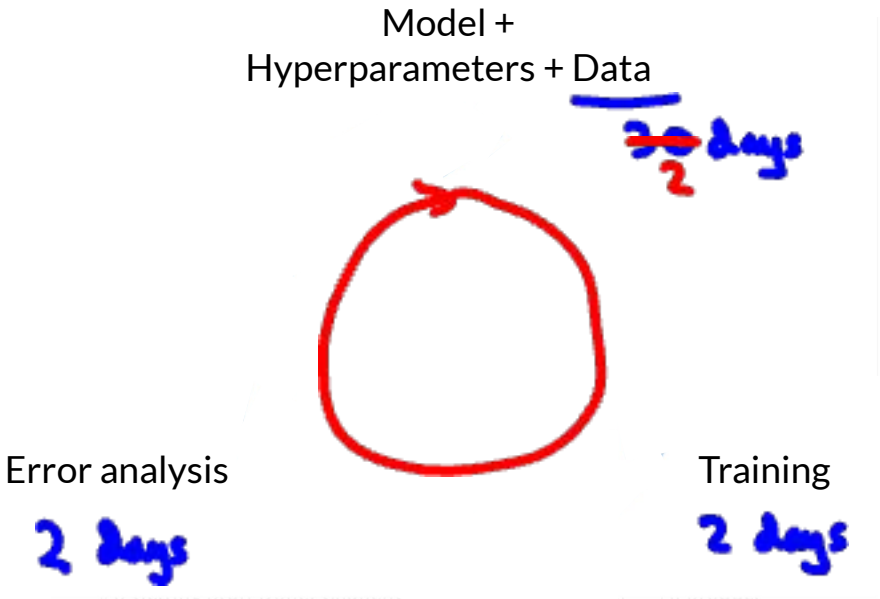
# Label and organize data

## Obtaining data

# How long should you spend obtaining data?




- Get into this iteration loop as quickly possible.
- Instead of asking: How long it would take to obtain $m$ examples?
  Ask: How much data can we obtain in $k$ days.
- Exception: If you have worked on the problem before and from experience you know you need $m$ examples.

# Inventory data

Brainstorm list of data sources (  speech recognition)

| Source | Amount | Cost | |
|---|---|---|---|
| Owned | 100h | $0 | ✓ |
| Crowdsourced – Reading | 1000h | $10000 | |
| Pay for labels | 100h | $6000 | |
| Purchase data | 1000h | $10000 | ✓ |

Other factors: Data quality, privacy, regulatory constraints

# Labeling data

- Options: In-house vs. outsourced vs. crowdsourced
- Having MLEs label data is expensive. But doing this for just a few days is usually fine.
- Who is qualified to label?

Speech recognition – any reasonably fluent speaker

Factory inspection, medical image diagnosis – SME (subject matter expert)

Recommender systems – maybe impossible to label well

- Don’t increase data by more than 10x at a time

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# Label and organize data

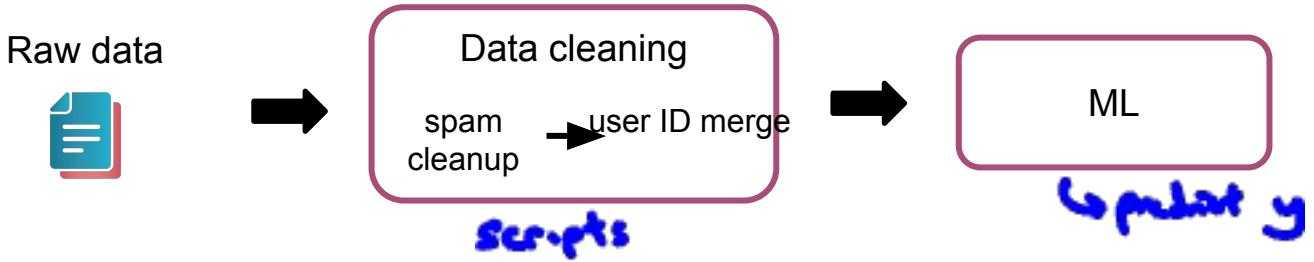
## Data pipeline

# Data pipeline example

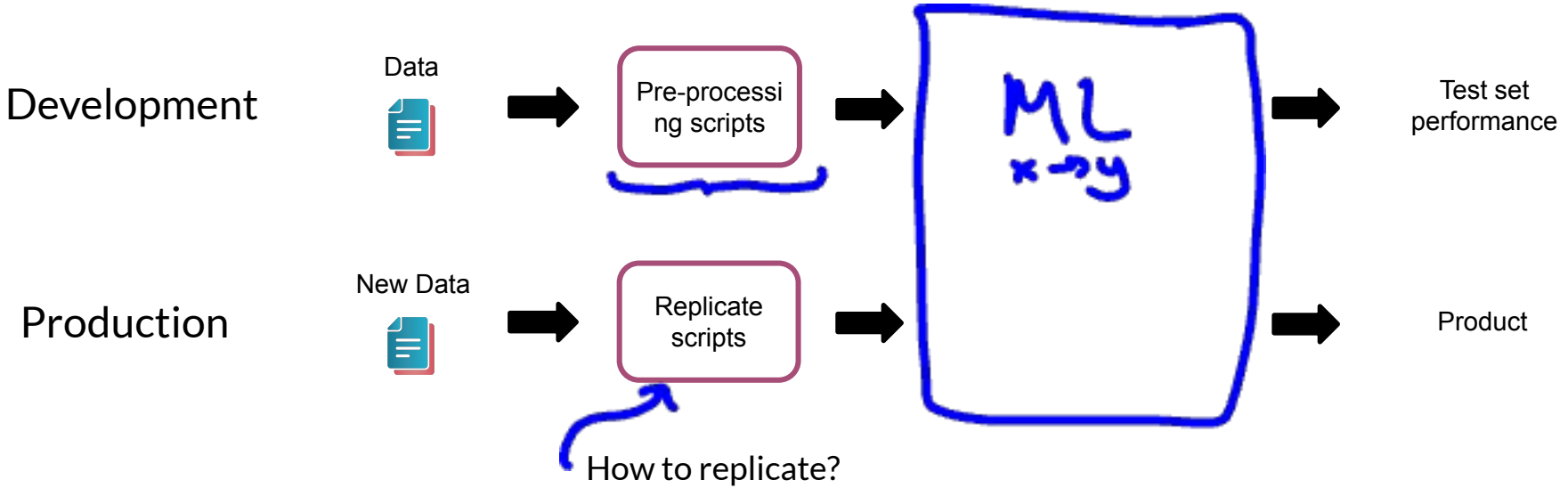
| | Job Board (website) | Resume chat (app) |
|---|---|---|
| Email | nova@deeplearning.ai | nova@chatapp.com |
| First Name | Nova | Nova |
| Last Name | Ng | Ng |
| Address | 1234 Jane Way | ? |
| State | CA | ? |
| Zip | 94304 | 94304 |

$x$ = user info

$y$ = looking for job



# Data pipeline example



# POC and Production phases

POC (proof-of-concept):

- Goal is to decide if the application is workable and worth deploying.
- Focus on getting the prototype to work!
- It's ok if data pre-processing is manual. But take extensive notes/comments.

Production phase:

- After project utility is established, use more sophisticated tools to make sure the data pipeline is replicable.
- E.g., TensorFlow Transform, Apache Beam, Airflow,….

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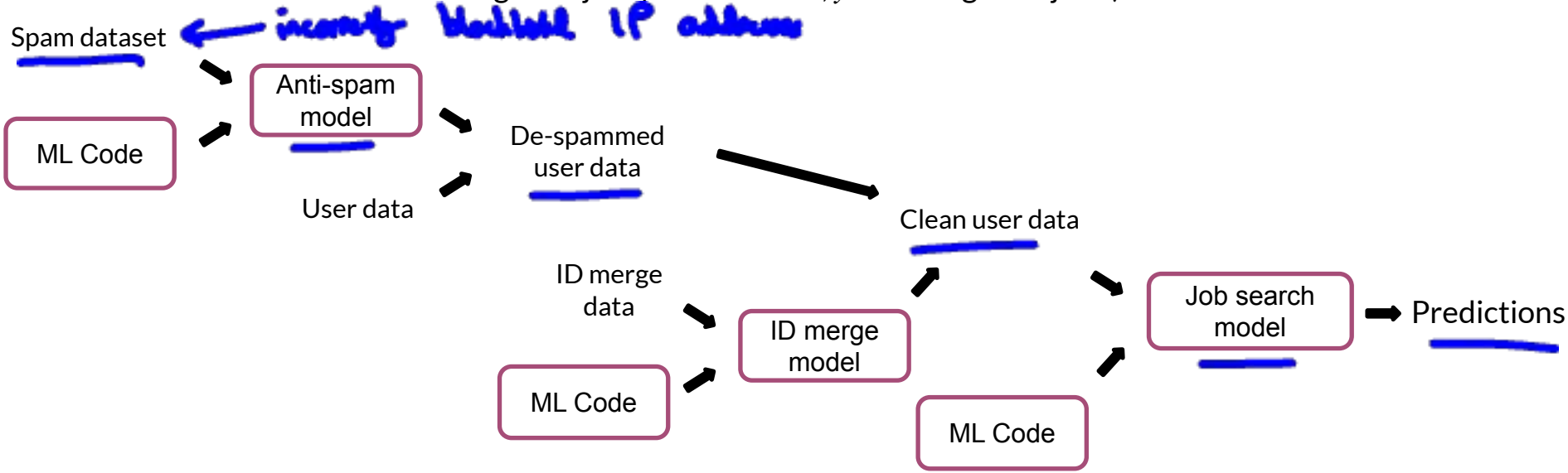
# Label and organize data

## Meta-data, data provenance and lineage

# Data pipeline example

Task: Predict if someone is looking for a job. ( $x$ = user data, $y$ = looking for a job? )




Keep track of data provenance and lineage

where it comes from

sequence of steps

# Meta-data

Examples:

Manufacturing visual inspection: Time, factory, line #, camera settings, phone model, inspector ID,....

Speech recognition: Device type, labeler ID, VAD model ID,....

Useful for:

- Error analysis. Spotting unexpected effects.
- Keeping track of data provenance.

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# Label and organize data

## Balanced train/dev/test splits

# Balanced train/dev/test splits in small data problems

**Visual inspection** example: 100 examples, 30 positive (defective)

Train/dev/test: 60% / 20% / 20%

Random split: 21 / 2 / 7 positive example

3% 1% 3%

Want: 18 / 6 / 6 } balanced split

30% / 30% / 30%

No need to worry about this with large datasets – a random split will be representative.

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# C1W3 Slides (Optional)

## Scoping

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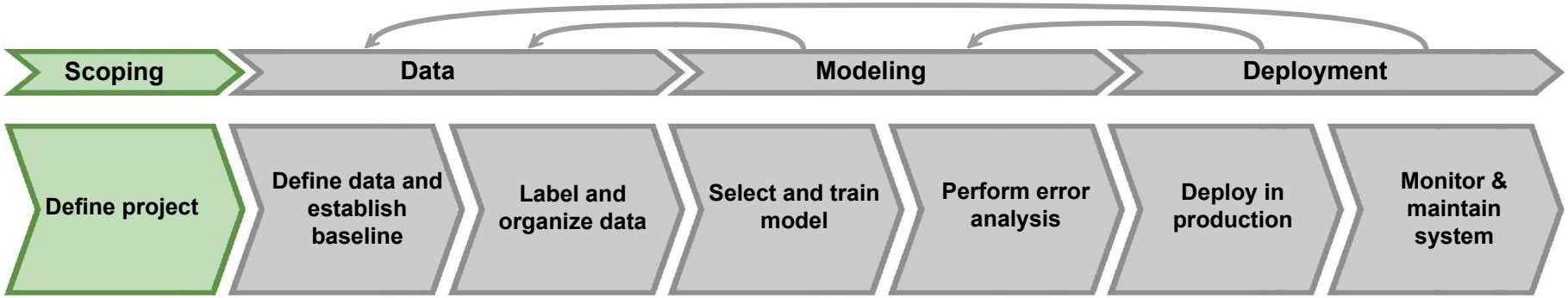
# Scoping (optional)

## What is scoping?




Scoping example: Ecommerce retailer looking to increase sales

- Better recommender system
- Better search
- Improve catalog data
- Inventory management
- Price optimization

Questions:

- What projects should we work on?
- What are the metrics for success?
- What are the resources (data, time, people) needed?

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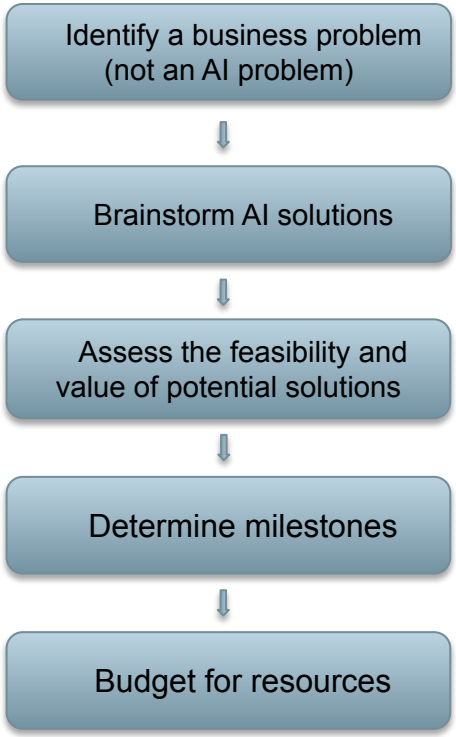
# Scoping (optional)

## Scoping process

# Scoping process




What are the top 3 things you wish were working better?

- Increase conversion
- Reduce inventory
- Increase margin (profit per item)

# Separating problem identification from solution

| Problem | Solution |
| --- | --- |
| Increase conversion | Search, recommendations |
| Reduce inventory | Demand prediction, marketing |
| Increase margin (profit per item) | Optimizing what to sell (e.g., merchandising), recommend bundles |
| What to achieve | How to achieve |

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# Scoping (optional)

## Diligence on feasibility and value

# Feasibility: Is this project technically feasible?

Use external benchmark (literature, other company, competitor)

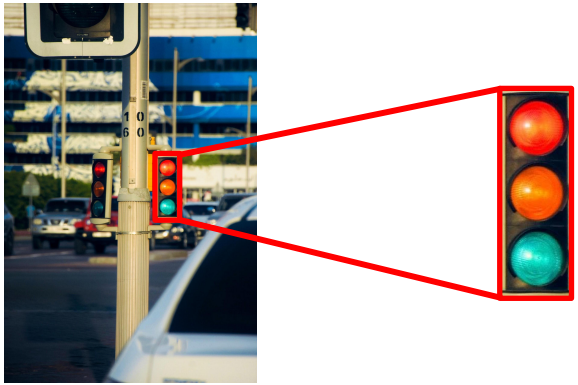
| | Unstructured (e.g., speech, images) | Structured (e.g., transactions, records) |
|---|---|---|
| New | HLP | Predictive features available? |
| Existing | HLP<br>History of project | New predictive features?<br>History of project |

HLP: Can a human, given the same data, perform the task?

# Why use HLP to benchmark?

People are very good on unstructured data tasks

Criteria: Can a human, given the same data, perform the task?

# Do we have features that are predictive?

x y

Given past purchases, predict future purchases ✓

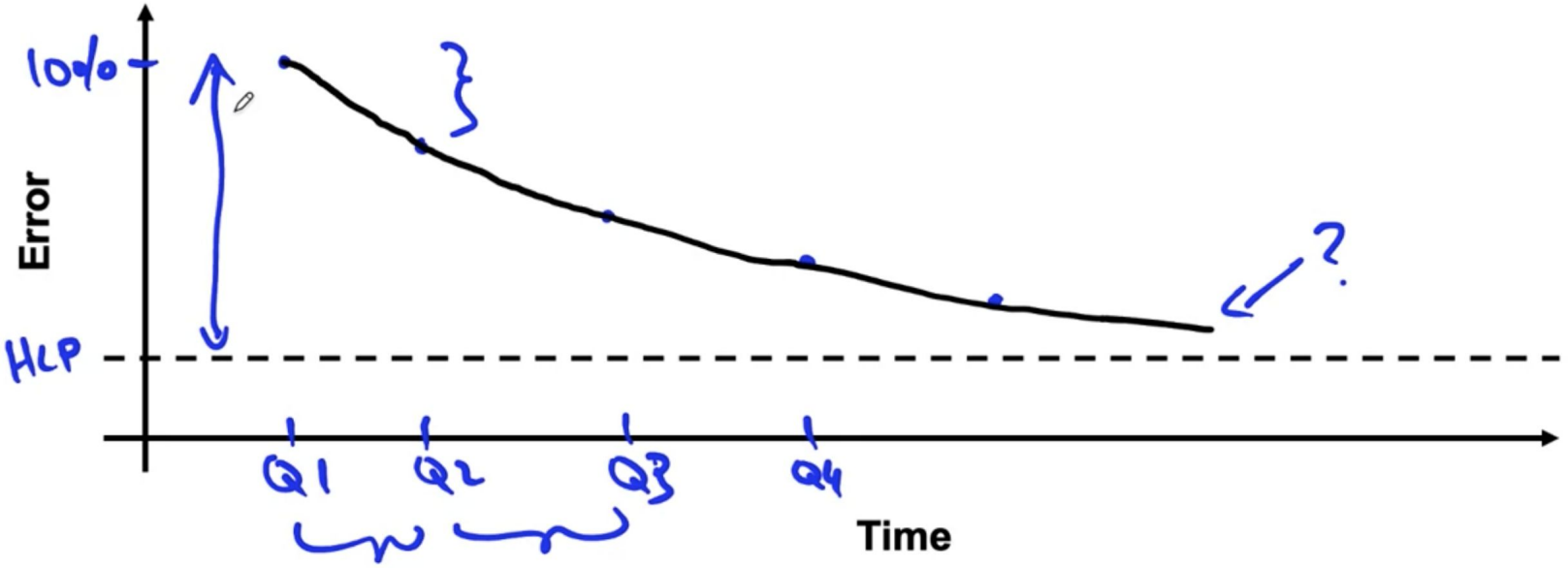
Given weather, predict shopping mall foot traffic ✓

Given DNA info, predict heart disease ?

Given social media chatter, predict demand for a clothing style ?

Given history of a stock's price, predict future price of that stock ✗

# History of project



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# Scoping (optional)

## Diligence on value

# Diligence on value


Have technical and business teams try to agree on metrics that both are comfortable with.

Fermi estimates

# Ethical considerations

- Is this project creating net positive societal value?
- Is this project reasonably fair and free from bias?
- Have any ethical concerns been openly aired and debated?

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# Scoping (optional)

## Milestones and resourcing

# Milestones

Key specifications:

- ML metrics (accuracy, precision/recall, etc.)
- Software metrics (latency, throughput, etc. given compute resources)
- Business metrics (revenue, etc.)
- Resources needed (data, personnel, help from other teams)

Timeline

If unsure, consider benchmarking to other projects, or building a POC (Proof of Concept) first.

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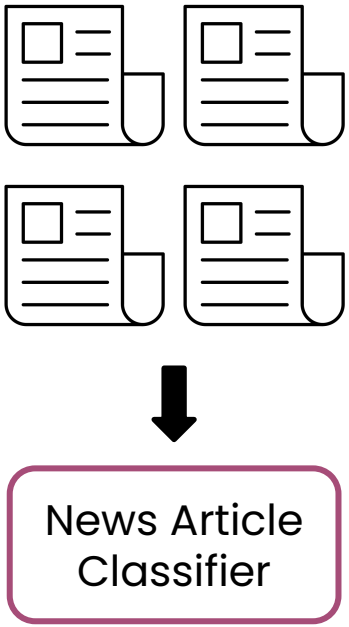
# Final project

# Final project overview

# Project overview

- Classify news articles
- Start from an existing prototype
- Iteratively improve the performance of the system



# Techniques

- Establish a baseline
- Balanced train/dev/test split
- Error analysis
- Track experiments
- Deploy using Tensorflow Serving

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