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C1W2 Slides

DeepLearning.AI

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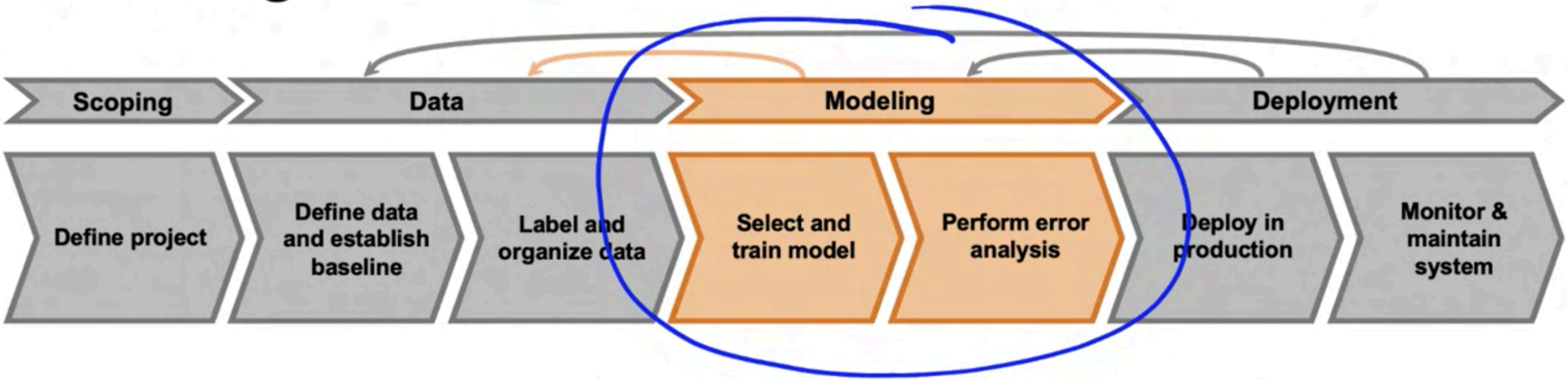
Select and train model

Modeling overview

Modeling



Model-centric AI development

Data-centric AI development

Select and train model

Key challenges

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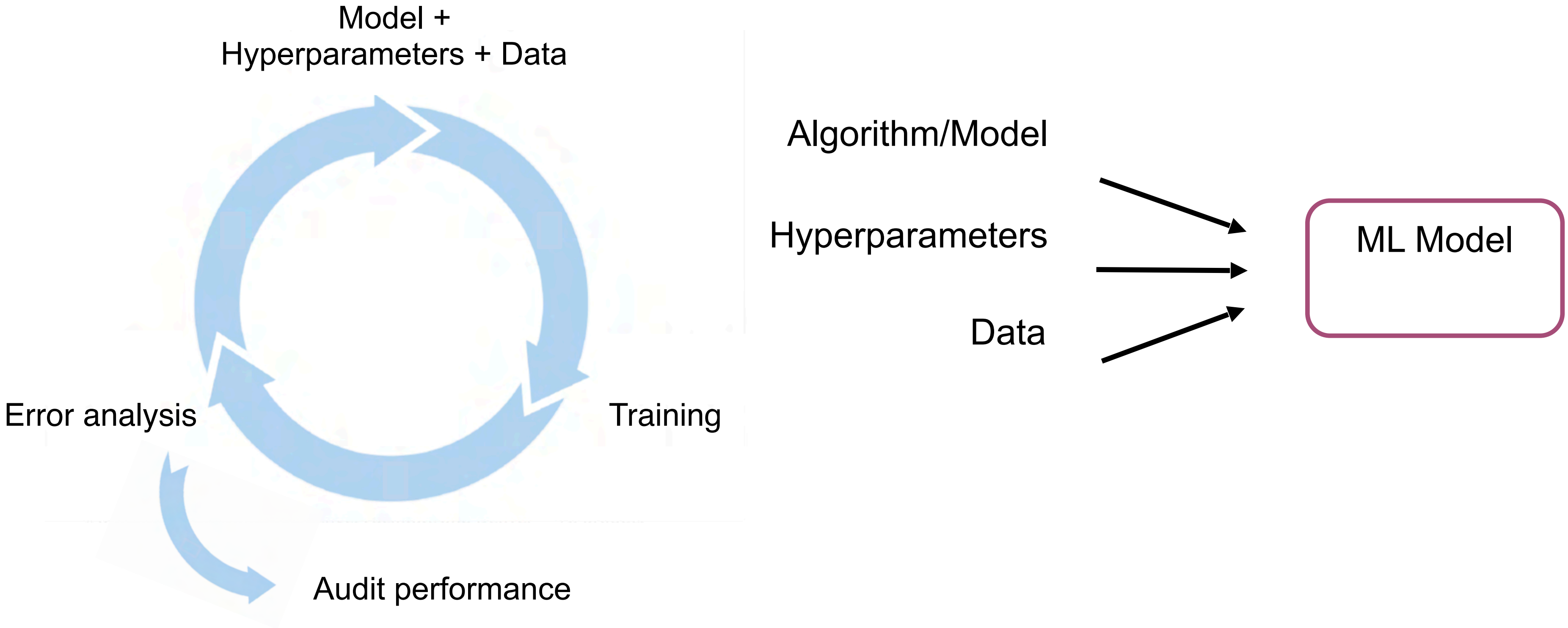
AI system = Code + Data

(algorithm/model)

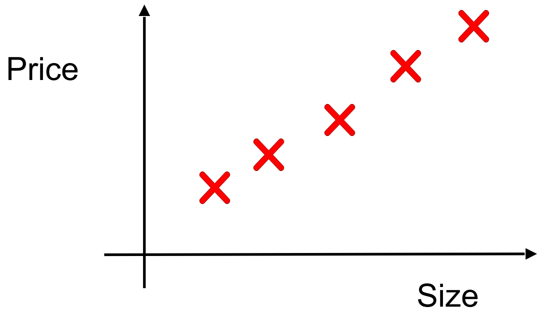
Model development is an iterative process



Challenges in model development

1. Doing well on training set (usually measured by average training error).

2. Doing well on dev/test sets.



3. Doing well on business metrics/project goals.

Select and train model

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Why low average test error isn't good enough

Performance on disproportionately important examples

Web Search example

"Apple pie recipe" "Latest movies"

"Wireless data plan" "Diwali festival"

Informational and Transactional queries

"Stanford" "Reddit" "Youtube"

Navigational queries

Performance on key slices of the dataset

Example: ML for loan approval

Make sure not to discriminate by ethnicity, gender, location, language or other protected attributes.

Example: Product recommendations from retailers

Be careful to treat fairly all major user, retailer, and product categories.

Rare classes

Skewed data distribution

99% negative   1% positive

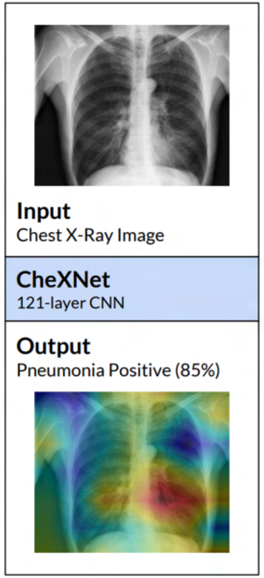
print("0") ←

Accuracy in rare classes

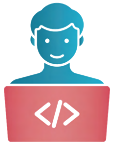
10,000 → Effusion

~100 → Hernia

Condition	Performance
Effusion	0.901
Edema	0.924
Mass	0.909
Hernia	0.851

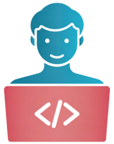


Unfortunate conversation in many companies



MLE: "I did well on the test set!"

Product Owner: "But this doesn't work for my application"



MLE: "But... I did well on the test set!"

Select and train model

Establish a baseline

Establishing a baseline level of performance

Speech recognition example:

Type	Accuracy	Human level performance	HLP
Clear Speech	94%	95%	1%
Car Noise	89%	93%	4%
People Noise	87%	89%	2%
Low Bandwidth	70%	70%	~0%

Structured and unstructured data

Unstructured data

Image

Audio

Text

This restaurant was great!

Structured Data

User Id	Purchase	Number	Price
3421	Blue shirt	5	$20
612	Brown shoes	1	$35

Price	Product
3421	Red skirt

Ways to establish a baseline

- Human level performance (HLP)
- Literature search for state-of-the-art/open source
- Older system

Baseline gives an estimate of the irreducible error / Bayes error and indicates what might be possible.

Select and train model

Tips for getting started

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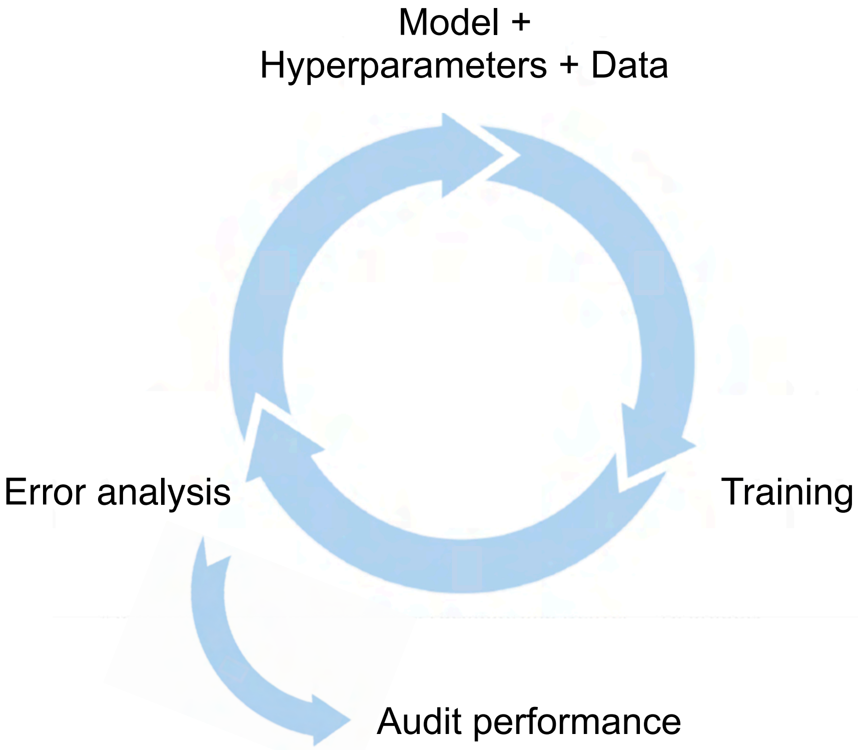
ML is an iterative process



Getting started on modeling

- Literature search to see what's possible.
- Find open-source implementations if available.
- A reasonable algorithm with good data will often outperform a great algorithm with not so good data.

Deployment constraints when picking a model

Should you take into account deployment constraints when picking a model?

Yes, if baseline is already established and goal is to build and deploy.

No, if purpose is to establish a baseline and determine what is possible and might be worth pursuing.

Sanity-check for code and algorithm

- Try to overfit a small training dataset before training on a large one.

- Example #1: Speech recognition

audio transcript

X ➡ Y

- Example #2: Image segmentation

- Example #3: Image classification

Error analysis and performance auditing

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Error analysis example

Speech recognition example

Example	Label	Prediction	Car Noise	People Noise	Low Bandwidth
1	"Stir fried lettuce recipe"	"Stir fry lettuce recipe"	✓		
2	"Sweetened coffee"	"Swedish coffee"		✓	✓
3	"Sail away song"	"Sell away some"		✓	
4	"Let's catch up"	"Let's ketchup"	✓	✓	✓

Iterative process of error analysis

Example

Propose tags

Visual inspection:

- Specific class labels (scratch, dent, etc.)
- Image properties (blurry, dark background, light background, reflection….)
- Other meta-data: phone model, factory

Product recommendations:

- User demographics
- Product features

Useful metrics for each tag

- What fraction of errors has that tag?
- Of all data with that tag, what fraction is misclassified?
- What fraction of all the data has that tag?
- How much room of improvement is there in that tag?

Error analysis and performance auditing

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Prioritizing what to work on

Prioritizing what to work on

Type	Accuracy	Human level performance	Gap to HLP	% of data
Clean Speech	94%	95%	1%	60% → 0.6%
Car Noise	89%	93%	4%	4% → 0.16%
People Noise	87%	89%	2%	30% → 0.6%
Low Bandwidth	70%	70%	0%	6% → ~0%

Prioritizing what to work on

Decide on most important categories to work on based on:

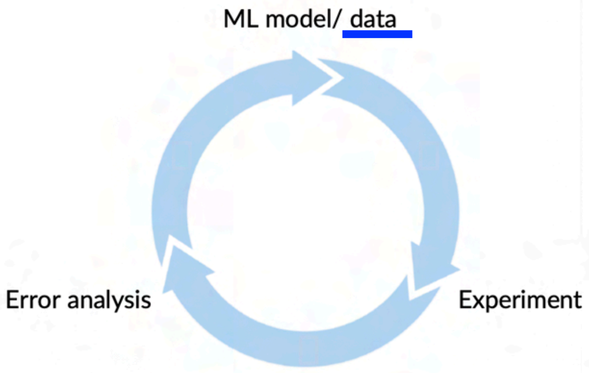
- How much room for improvement there is.
- How frequently that category appears.
- How easy is to improve accuracy in that category.
- How important it is to improve in that category.

Adding data

For categories you want to prioritize:

- Collect more data (or improve label accuracy)
- Use data augmentation to get more data

Type	Accuracy	Human level performance	Gap to HLP	% of data
Clean Speech	94%	95%	1%	60%
Car Noise	84%	93%	4%	40%
People Noise	87%	84%	2%	30%
Low Bandwidth	70%	70%	0%	6%



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Error analysis and performance auditing

Skewed datasets

Examples of skewed datasets

Manufacturing example

99.7% no defect $y=0$

0.3% defect $y=1$

print("0")
99.7%

Medical Diagnosis example: 98% of patients don't have a disease

Speech Recognition example: In wake word detection, 96.7% of the time wake word doesn't occur

Confusion matrix: precision and recall

Actual

Predicted	y=0	y=1
y=0	905 TN	18 FN
y=1	9 FP	68 TP
	↳ 914	↳ 86

TN: True Negative

TP: True Positive

FN: False Negative

FP: False Positive

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{68}{68+9} = 88.3\%$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{68}{68+18} = 79.1\%$$

What happens with print("0")?

		Actual y = 0	Actual y = 1
Predicted	y = 0	914	86 FN
Predicted	y = 1	0 FP	0 TP

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{0}{0+0}$$

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{0}{0+86} = 0\%$$

Combining precision and recall – F_1 score

	Precision (P)	Recall (R)	F_1
Model 1	88.3	79.1	83.4 %
Model 2	97.0	7.3	13.6 %

$$F_1 = \frac{2}{\frac{1}{P} + \frac{1}{R}}$$

Multi-class metrics

Classes: Scratch, Dent, Pit mark, Discoloration

Defect Type	Precision	Recall	F_1
Scratch	82.1%	99.2%	89.8%
Dent	92.1%	99.5%	95.7%
Pit mark	85.3%	98.7%	91.5%
Discoloration	72.1%	97%	82.7%

Error analysis and performance auditing

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Performance auditing

Auditing framework

Check for accuracy, fairness and bias.

1. Brainstorm the ways the system might go wrong.
   - Performance on subsets of data (e.g., ethnicity, gender).
   - Prevalence of specific errors/outputs (e.g., FP, FN).
   - Performance on rare classes.

2. Establish metrics to assess performance against these issues on appropriate slices of data.

3. Get business/product owner buy-in.

Speech recognition example

1. Brainstorm the ways the system might go wrong.
    - Accuracy on different genders and ethnicities.
    - Accuracy on different devices.
    - Prevalence of rude mistranscriptions.

2. Establish metrics to assess performance against these issues on appropriate slices of data.
    - Mean accuracy for different genders and major accents.
    - Mean accuracy on different devices.
    - Check for prevalence of offensive words in the output.

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Data iteration

Data-centric AI development

Data-centric AI development

Model-centric view

Collect what data you can, and develop a model good enough to deal with the noise in the data.

Hold the data fixed and iteratively improve the code/ model.

Data-centric view

The consistency of the data is paramount. Use tools to improve the data quality; this will allow multiple models to do well.

Hold the code fixed and iteratively improve the data.

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Data iteration

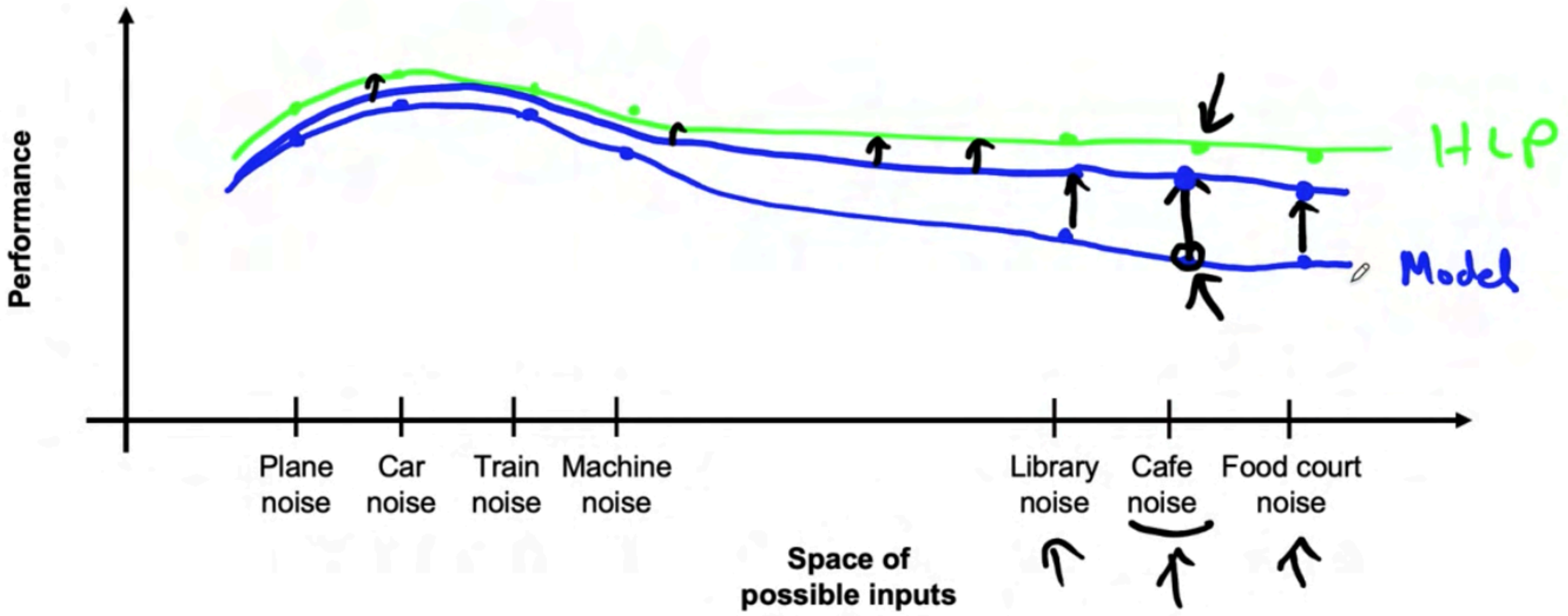
A useful picture of data augmentation

Speech recognition example

Different types of speech input:

- Car noise
- Plane noise
- Train noise
- Machine noise
- Cafe noise
- Library noise
- Food court noise

Speech recognition example



Data iteration

Data augmentation

Data augmentation

Goal:

Create realistic examples that (i) the algorithm does poorly on, but (ii) humans (or other baseline) do well on

Checklist:

- Does it sound realistic?
- Is the X → Y mapping clear? (e.g., can humans recognize speech?)
- Is the algorithm currently doing poorly on it?

The rubber sheet analogy

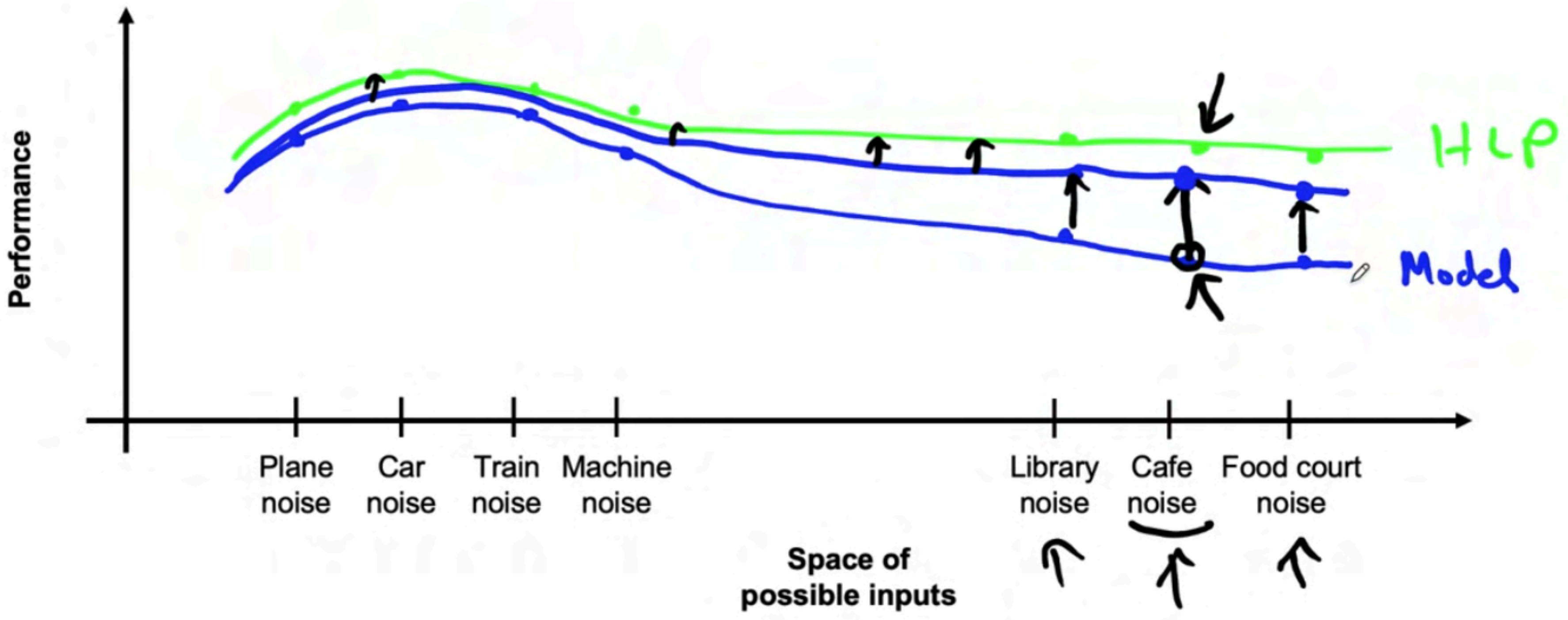
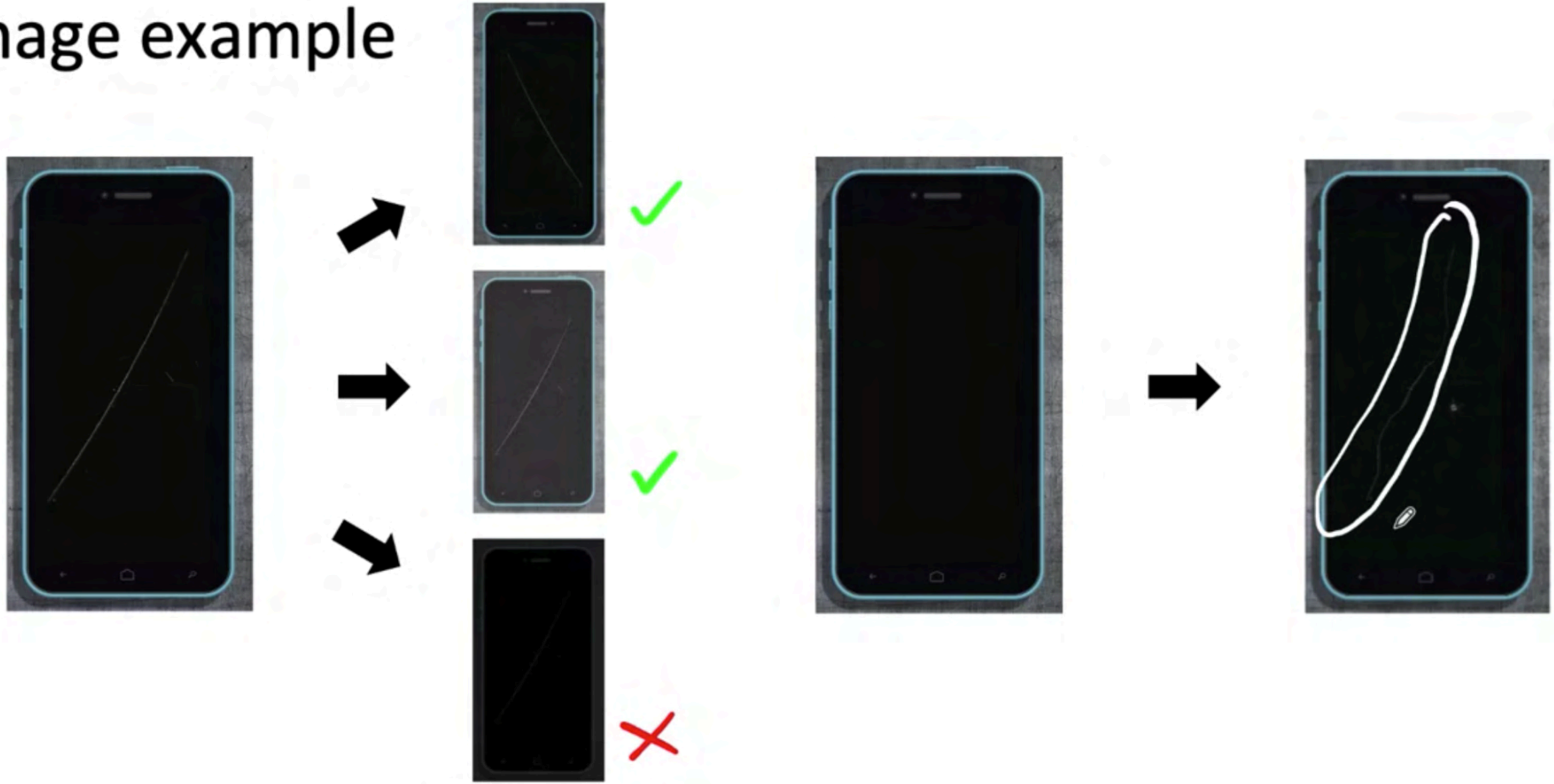
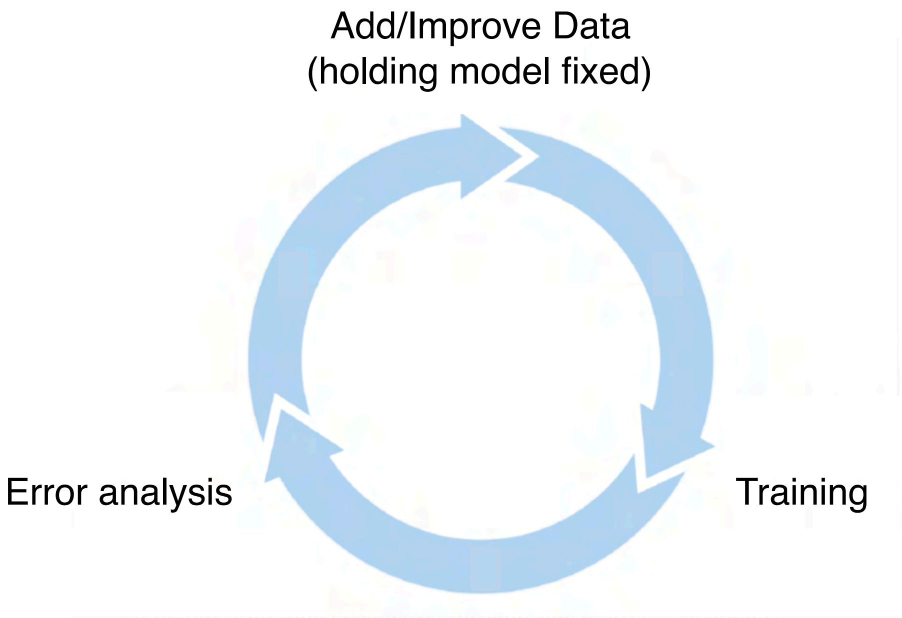


Image example



Data iteration loop



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Data iteration

Can adding data hurt?

Can adding data hurt performance?

For unstructured data problems, if:

- The model is large (low bias).
- The mapping X → Y is clear (e.g., humans can make accurate predictions).

Then, **adding data rarely hurts accuracy.**

Photo OCR counterexample

1

high accuracy

I

42I

low accuracy

1? I?

Adding a lot of new "I"s may skew the dataset and hurt performance

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Data iteration

Adding features

Structured data

Restaurant recommendation example

Vegetarians are frequently recommended restaurants with only meat options.

Possible features to add?

- Is person vegetarian (based on past orders)?
- Does restaurant have vegetarian options (based on menu)?

Other food delivery examples

- Only tea/coffee
- Only pizza

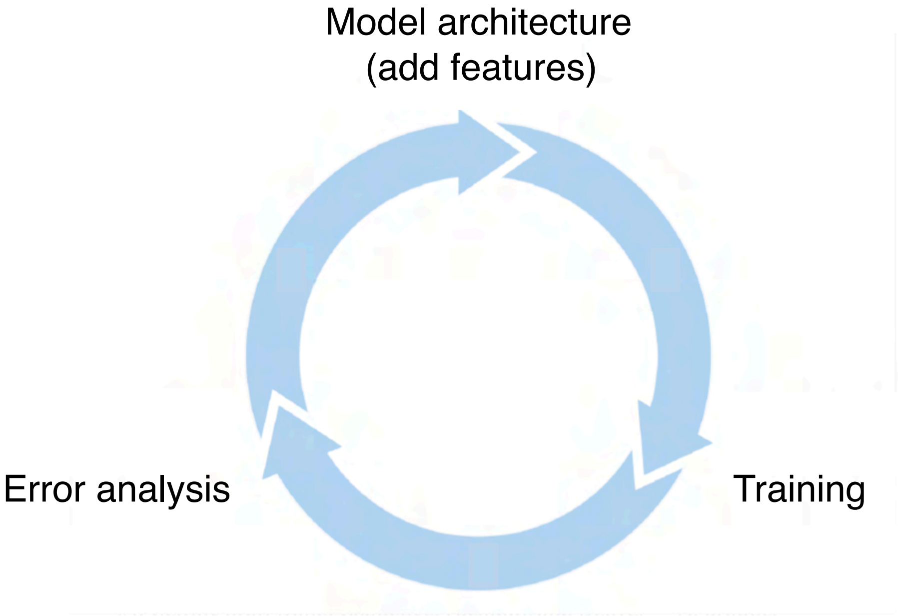
What are the added signals (features) that can help make a decision?

Product recommendation:

Collaborative filtering

Context based filtering

Data iteration



- Error analysis can be harder if there is no good baseline (such as HLP) to compare to.

- Error analysis, user feedback and benchmarking to competitors can all provide inspiration for features to add.

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Data iteration

Experiment tracking

Experiment tracking

What to track?

- Algorithm/code versioning
- Dataset used
- Hyperparameters
- Results

Tracking tools

- Text files
- Spreadsheet
- Experiment tracking system

Desirable features

- Data needed to replicate results
- In-depth analysis of experiment results
- Perhaps also: Resource monitoring, visualization, model error analysis

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Data iteration

From big data to good data

From Big Data to Good Data

Try to ensure consistently high-quality data in all phases of the ML project lifecycle.

Good data is:

- Cover of important cases (good coverage of inputs x)
- Defined consistently (definition of labels y is unambiguous)
- Has timely feedback from production data (distribution covers data drift and concept drift)
- Sized appropriately