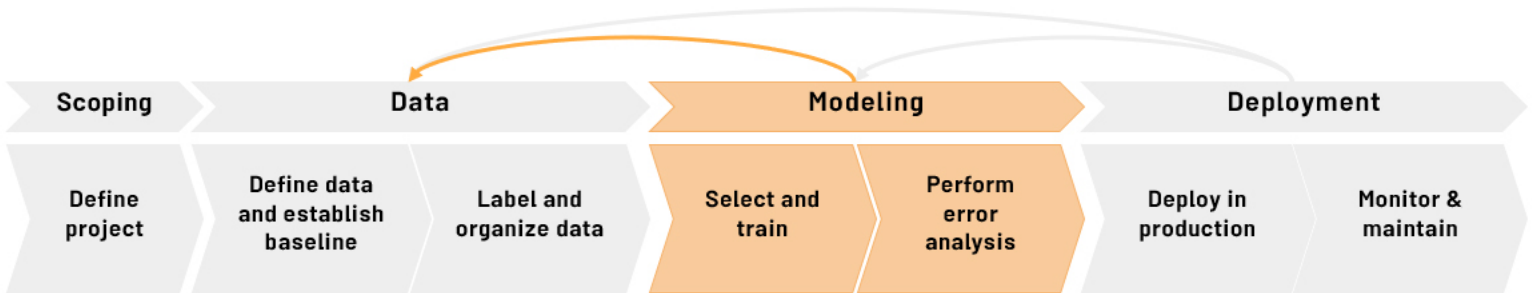
ML in Production

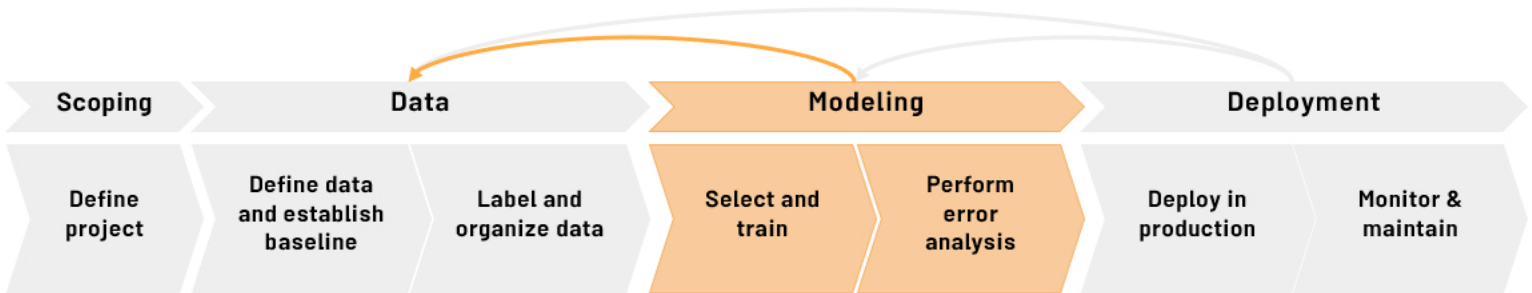
Part 2: Select and Train a Model

Ramin Toosi

Modeling

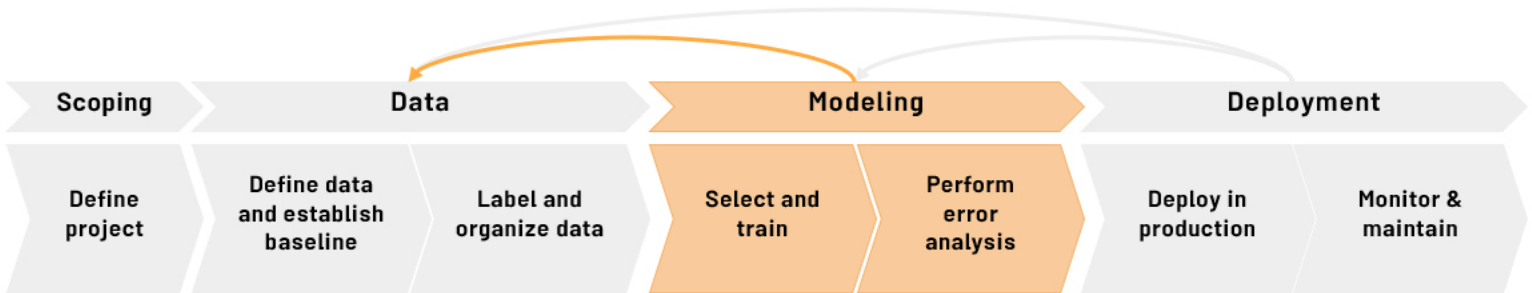

Scoping
Data
Modeling
Deployment
Define project
Define data and establish baseline
Label and organize data
Select and train
Perform error analysis
Deploy in production
Monitor & maintain

Modeling



Model centric AI development

Modeling



Model centric AI development

Data centric AI development

Key challenges

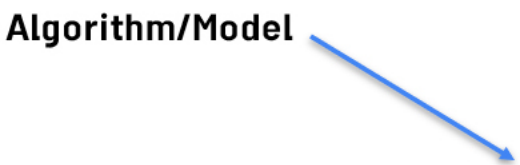
AI system = Code + Data

Key challenges

AI system = Code + Data

(algorithm/model)

Model development is an iterative process



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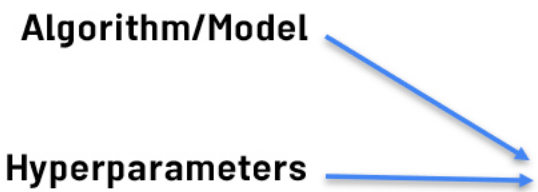

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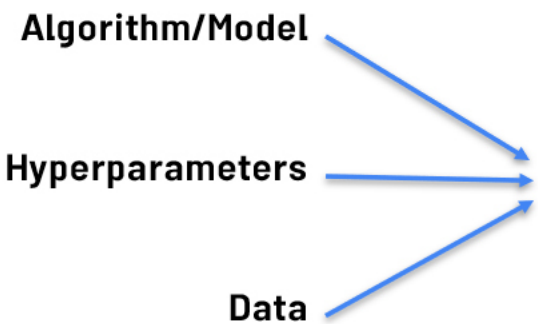

Model development is an iterative process

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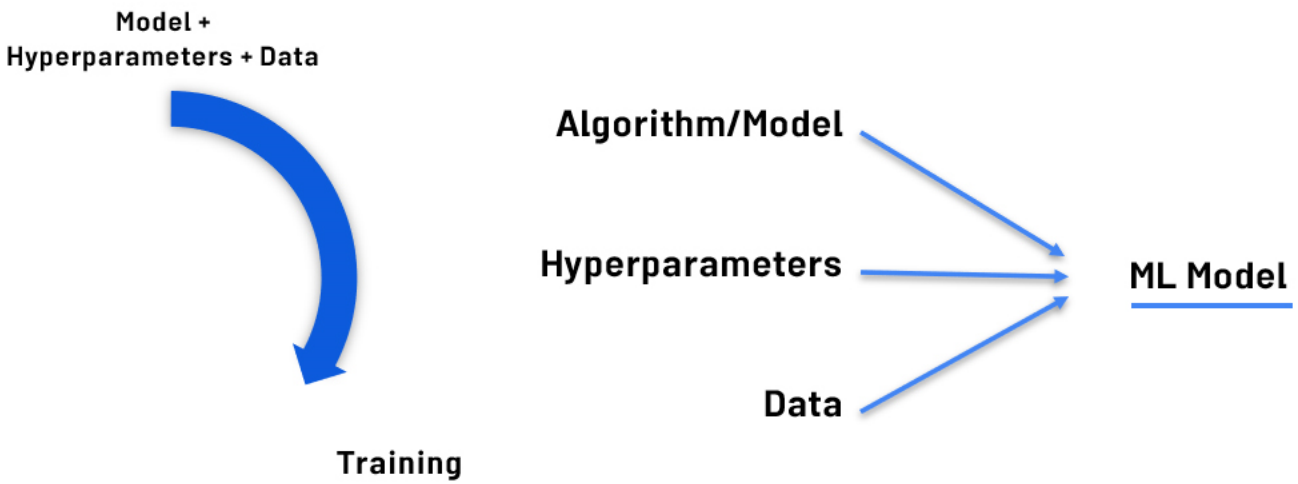
Model +
Hyperparameters + Data

Model development is an iterative process



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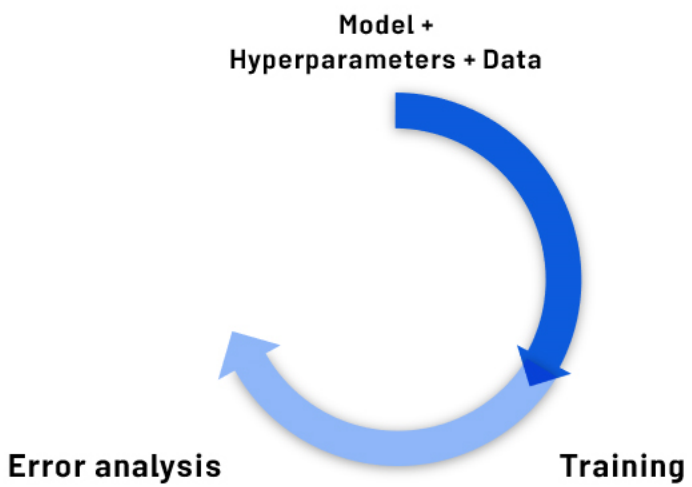

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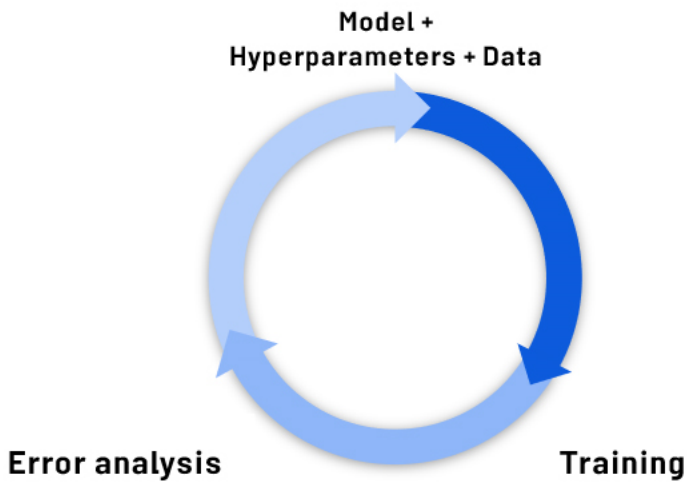
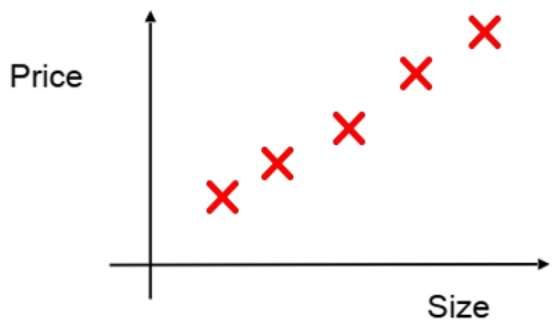


Challenges in model development

- Doing well on training set (usually measured by average training error).
- Doing well on dev/test sets.
- Doing well on business metrics/project goals.



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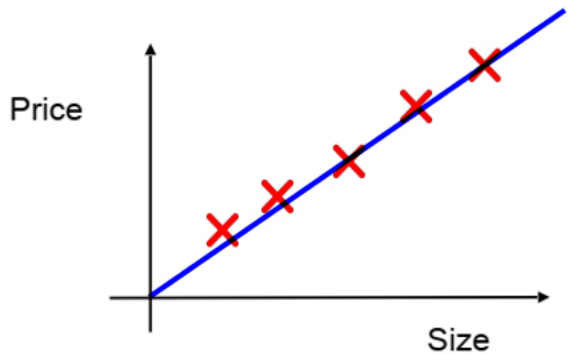
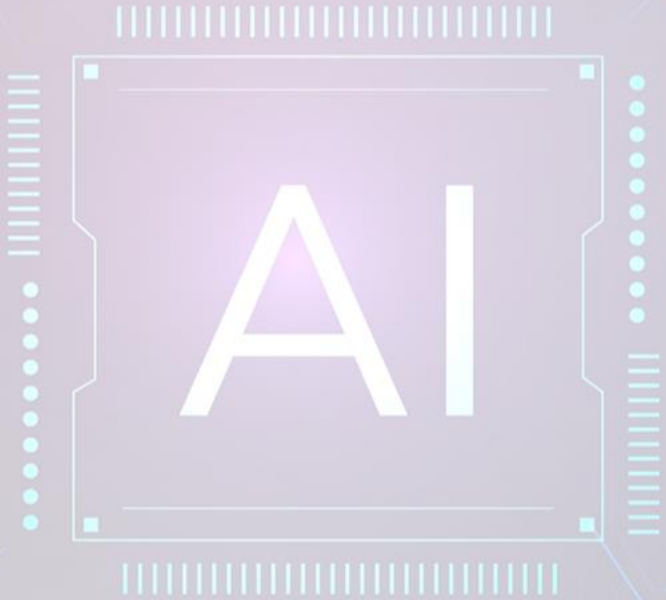


Why low average test error isn't good enough



Performance on disproportionately important example

Web Search example

"Apple pie recipe"

"Diwali festival"

"Latest movies"

"Wireless data plan"

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Informational and

Transactional queries

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Informational and
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"Stanford" "Reddit" "Youtube"

Performance on disproportionately important example

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"Apple pie recipe"
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Informational and Transactional queries

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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.

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”) !

Rare classes

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Accuracy in rare classes

Rare classes

- Skewed data distribution
  - 99% negative
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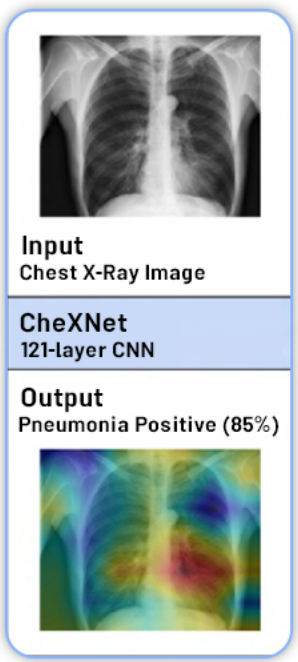
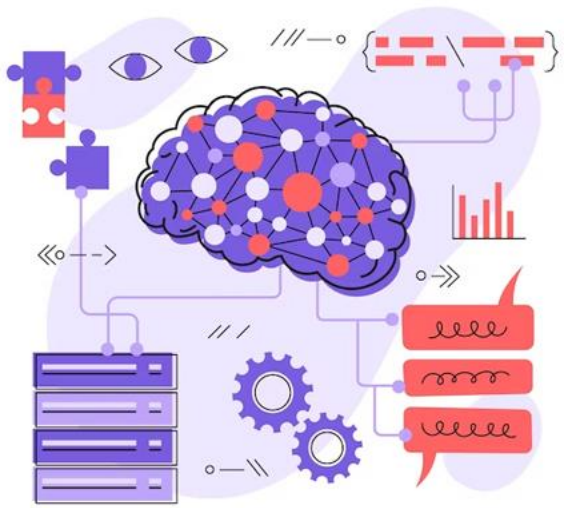
Accuracy in rare classes

Condition	Performance
Effusion	0.901
Edma	0924
Mass	0.909
Hernia	0.751



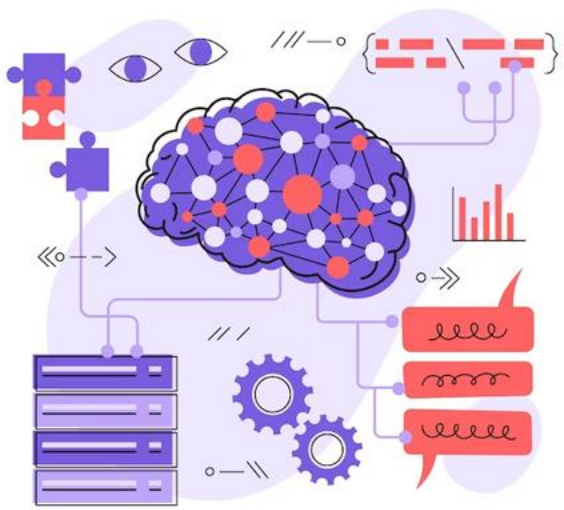
Unfortunate conversation in many companies

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



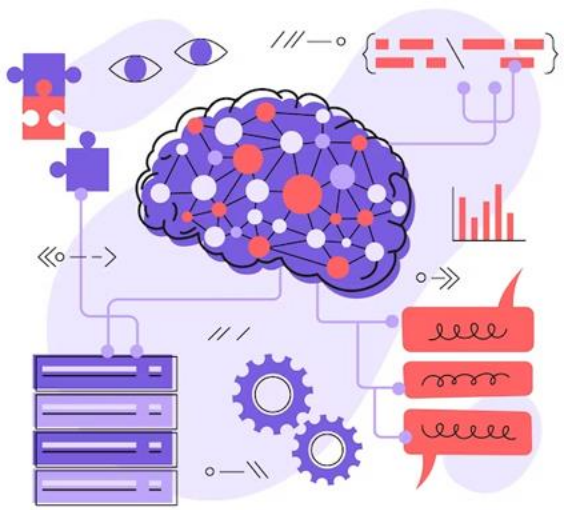
Unfortunate conversation in many companies

- MLE: "I did well on the test set!"
- Product Owner: "But this doesn't work for my application"

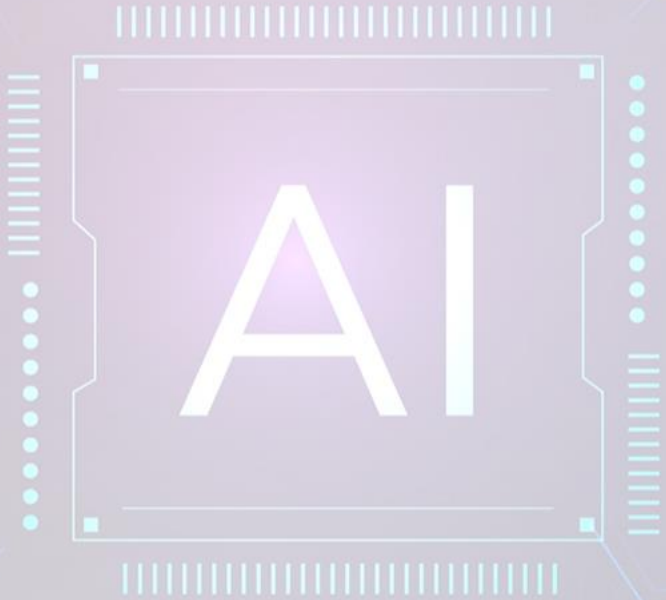


Unfortunate conversation in many companies

- 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!"



Establish a baseline



Establishing a baseline level of performance

Speech recognition example

Type	Accuracy
Clear Speech	94%
Car Noise	89%
People Noise	87%
Low Bandwidth	70%

Establishing a baseline level of performance

Speech recognition example

Type	Accuracy	Human Level Performance
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!

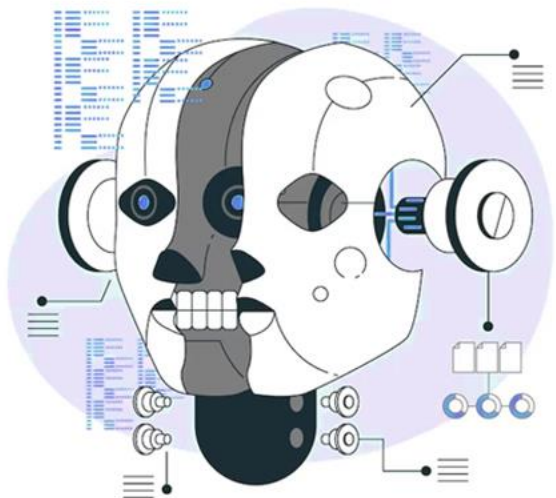
Structured Data

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

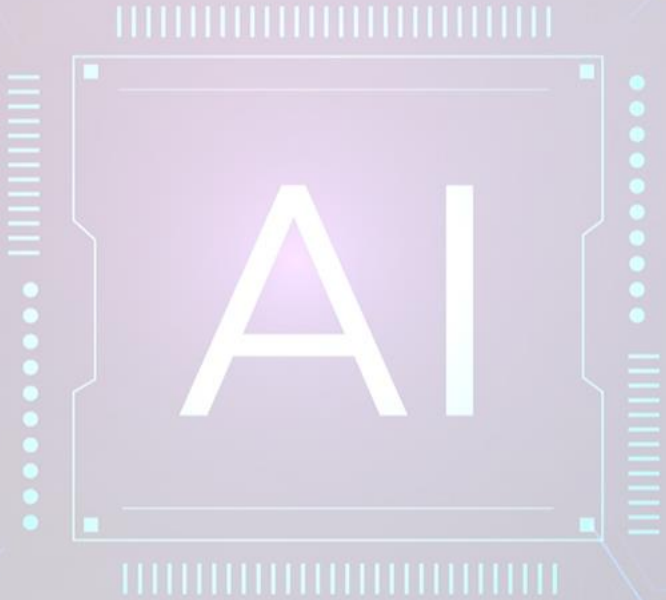
Ways to establish a baseline

- 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.

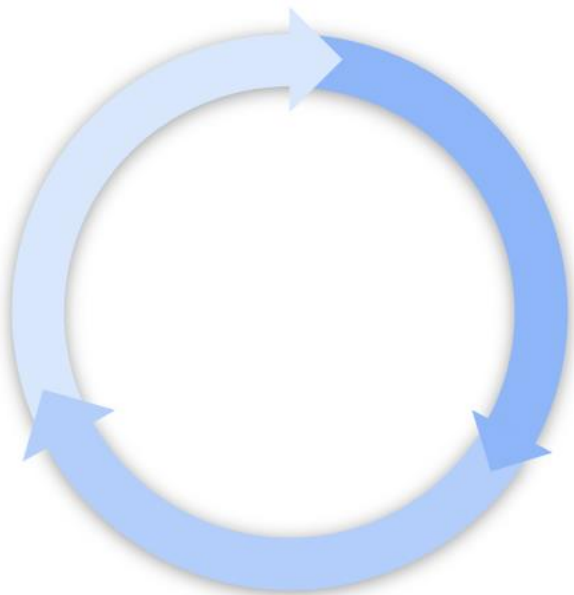


Tips for Getting Started a ML Project



ML is an iterative process

Model +
Hyperparameters + Data

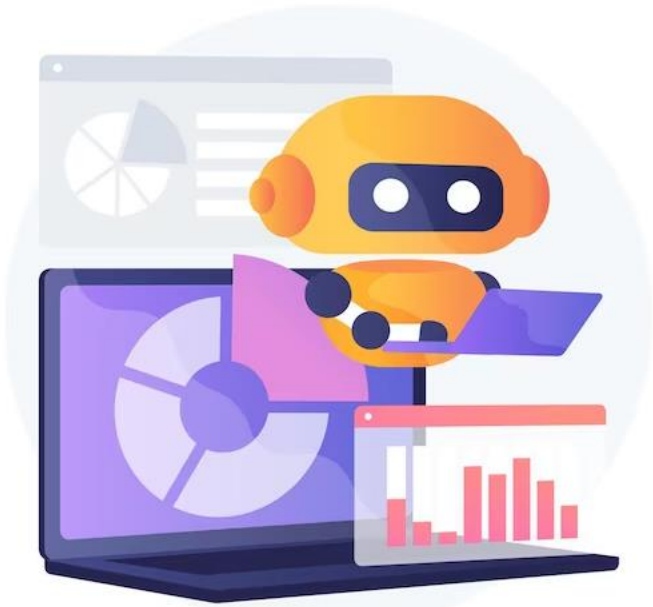


Training

Error analysis

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

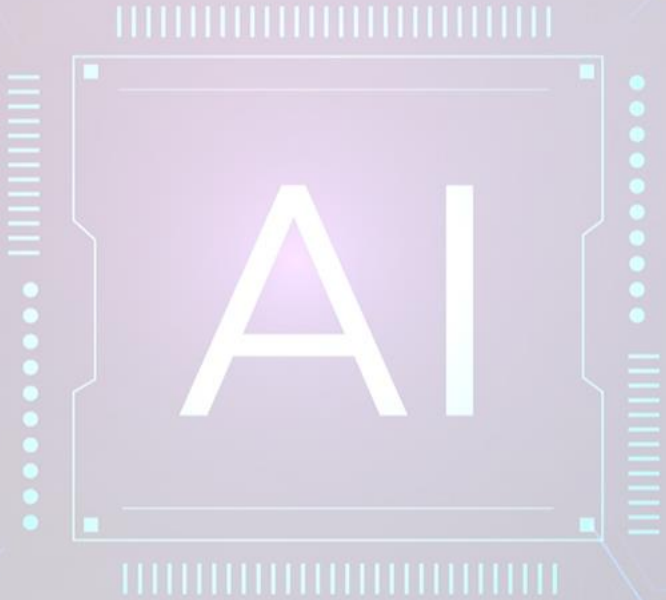
- Try to overfit a small training dataset before training on a large one.
- Example #1: Speech recognition
- Example #2: Image segmentation
- Example #3: Image classification

audio

transcript ␣ ␣ ␣ ␣ ␣ ␣

X→Y

Error analysis and performance auditing



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"			

Speech recognition example

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Iterative process of error analysis

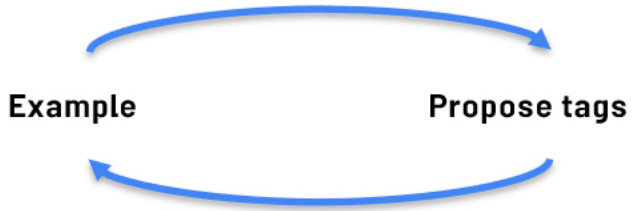
Example	Propose tags

Iterative process of error analysis

Example

Propose tags

Iterative process of error analysis



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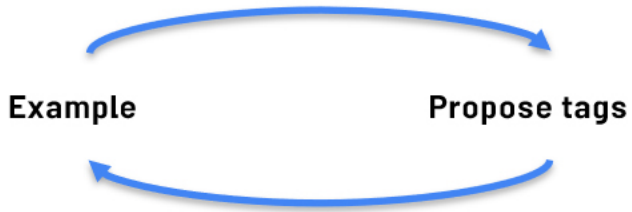
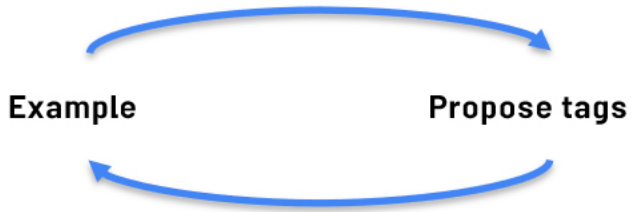


- **Visual inspection:**
  - Specific class labels (scratch, dent, etc.)
  - Image properties (blurry, dark background, light background, reflection….)
  - Other meta-data: phone model, factory

Iterative process of error analysis



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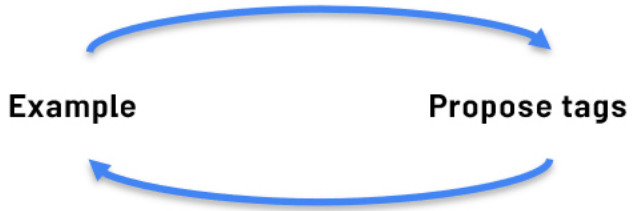

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  - Specific class labels (scratch, dent, etc.)
  - Image properties (blurry, dark
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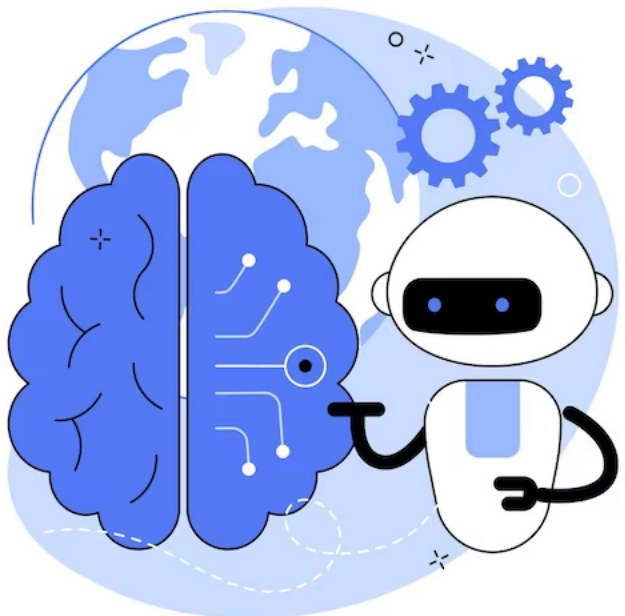
- **Product recommendations:**
  - User demographics
  - Product features

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?



Prioritizing what to work on

Type	Accuracy	HLP
Clear Speech	94%	95% (1%)
Car Noise	89%	93% (4%)
People Noise	87%	89% (2%)
Low Bandwidth	70%	70% (0%)

Prioritizing what to work on

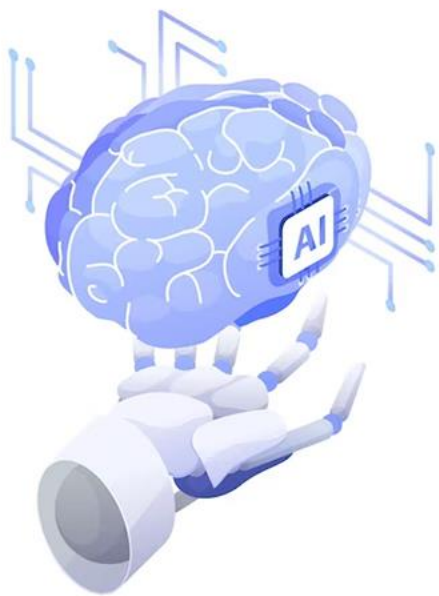
Type	Accuracy	HLP	% data
Clear Speech	94%	95% (1%)	60
Car Noise	89%	93% (4%)	4
People Noise	87%	89% (2%)	30
Low Bandwidth	70%	70% (0%)	6

Prioritizing what to work on

Type	Accuracy	HLP	% data	Improvement
Clear 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/improving data for specific categories

- **For categories you want to prioritize:**
  - Collect more data
  - Use data augmentation to get more data
  - Improve label accuracy / data quality

Skewed datasets

- **Manufacturing** example 
  - 99.7% no defect
  - 0.3% defect
- **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

Predicted \ Actual	Y = 0	Y = 1
Y = 1	905 TN	18 FN
Y = 0	9 FP	68 TP

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

What happens with print("0")?

Predicted \ Actual	Y = 0	Y = 1
Y = 1	914 TN	86 FN
Y = 0	0 FP	0 TP

Precision = TP / (TP + FP) = 0/0

Recall = TP / (TP + FN) = 0/86 = 0

Combining precision and recall – F_1 score

	Precision	Recall	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

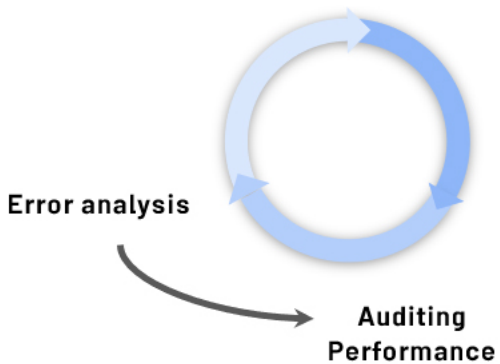
Defect Type	Precision	Recall	F_1
Scratch	82.1%	99.2%	89.8%
Dent	92.1%	99.5%	95.7%
Pit mark	85.3%	98.7%	91.5%
Discoloration	72.1%	97%	82.7%

Performance Auditing framework

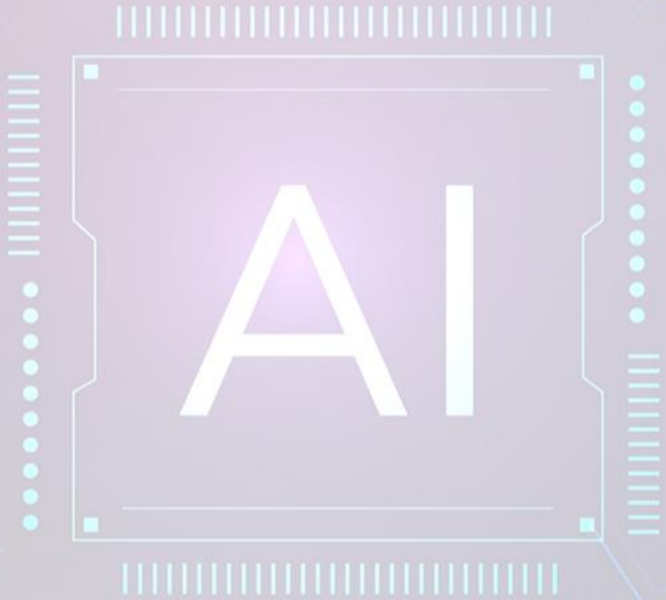
- Check for accuracy, fairness and bias.
- 1. Brainstorm the ways the system might go wrong.
  - Performance on subsets of data (e.g., ethnicity, gender).
  - Prevalence of specific errors/outputs (e.g., FP, FN).
  - Performance on rare classes.
- 2. Establish metrics to assess performance against these issues on appropriate slices of data.
- 3. Get business/product owner buy-in.

Speech recognition example

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



Data-centric AI development



Data-centric AI development

- Model-centric view

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.

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Data-centric view

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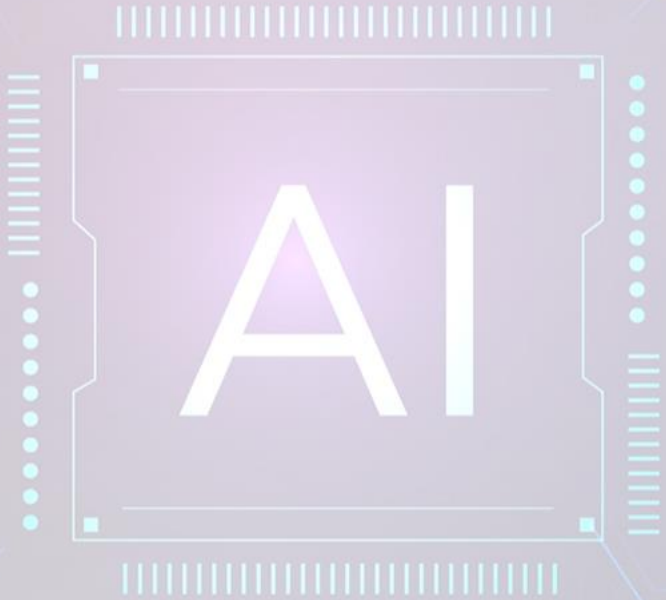
Data-centric view

- 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.

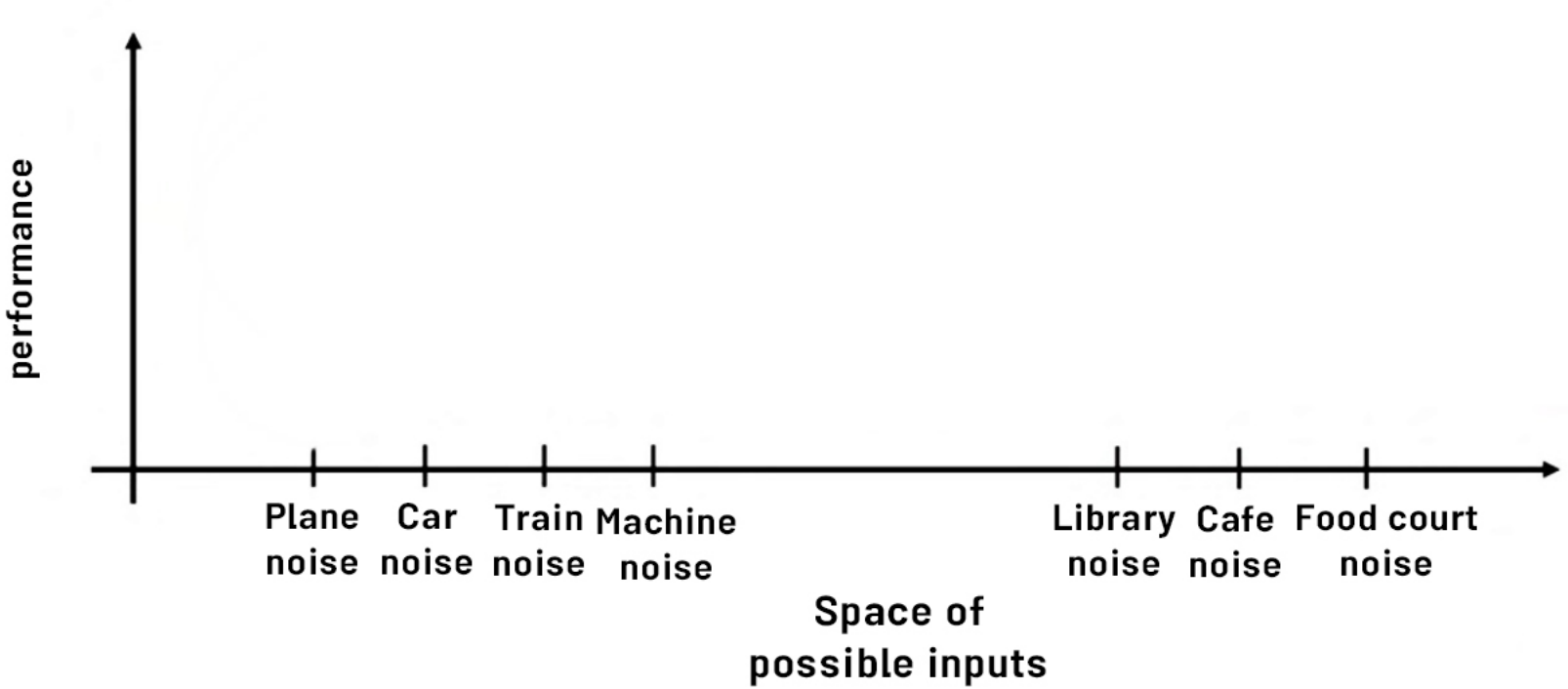
A useful picture of data augmentation



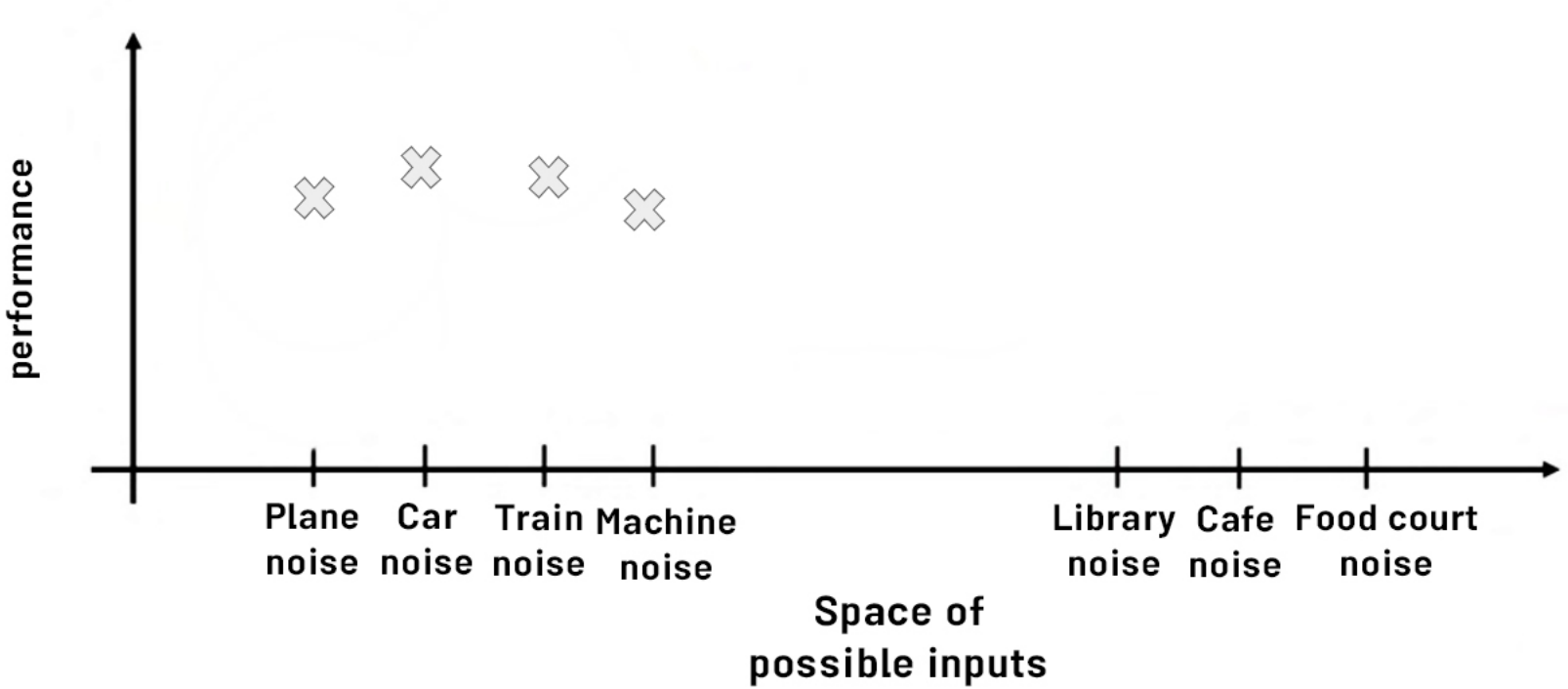
Speech Recognition example

- **Different types of speech input:**
  - Car noise
  - Plane noise
  - Train noise
  - Machine noise
  - Cafe noise
  - Library noise
  - Food court noise

Speech Recognition example



Speech Recognition example



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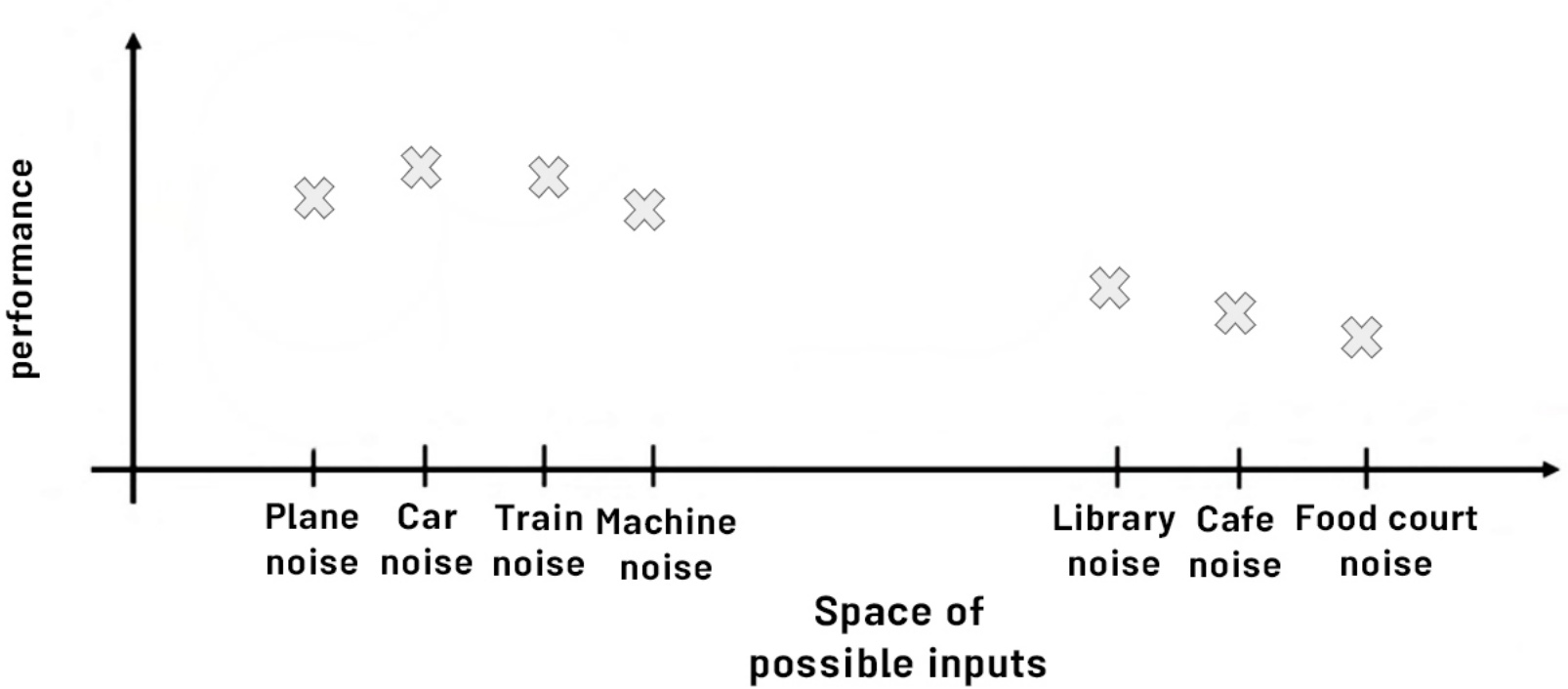

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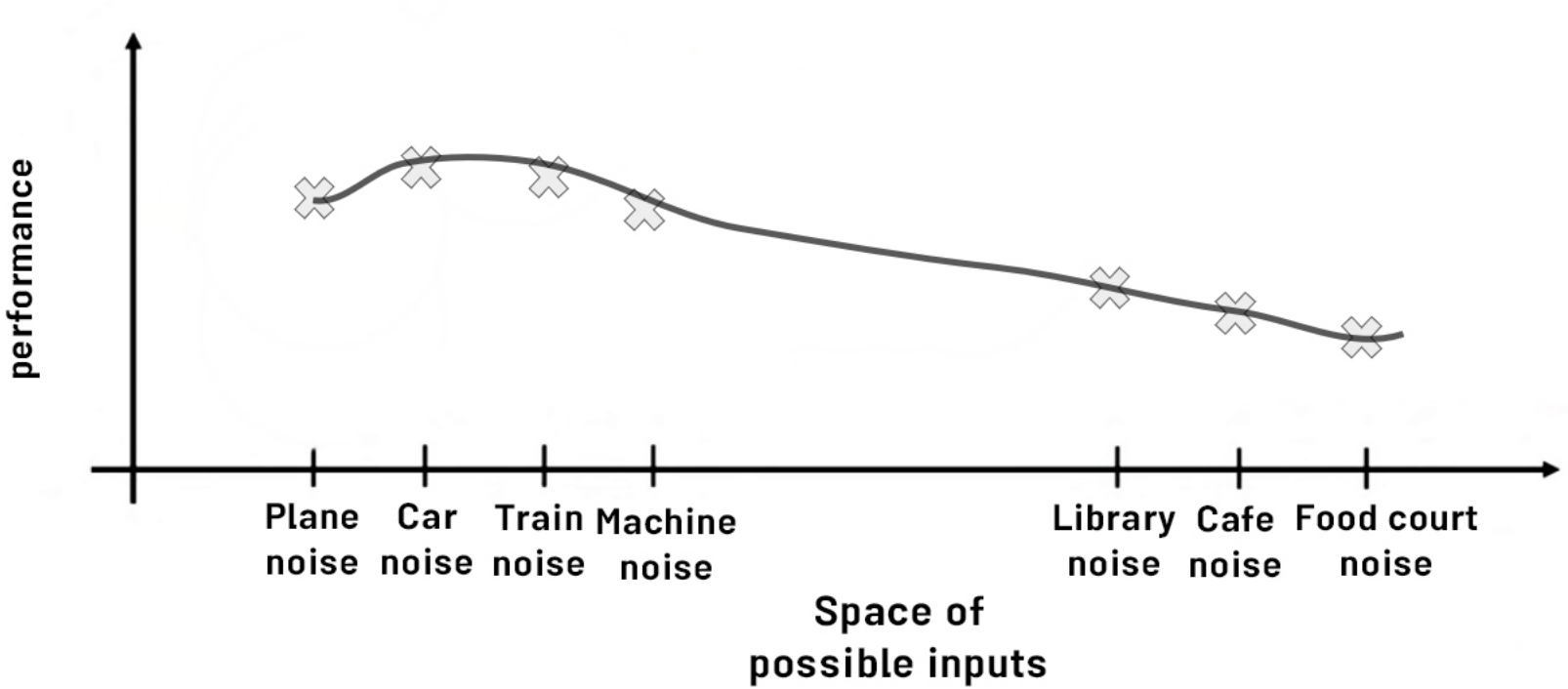

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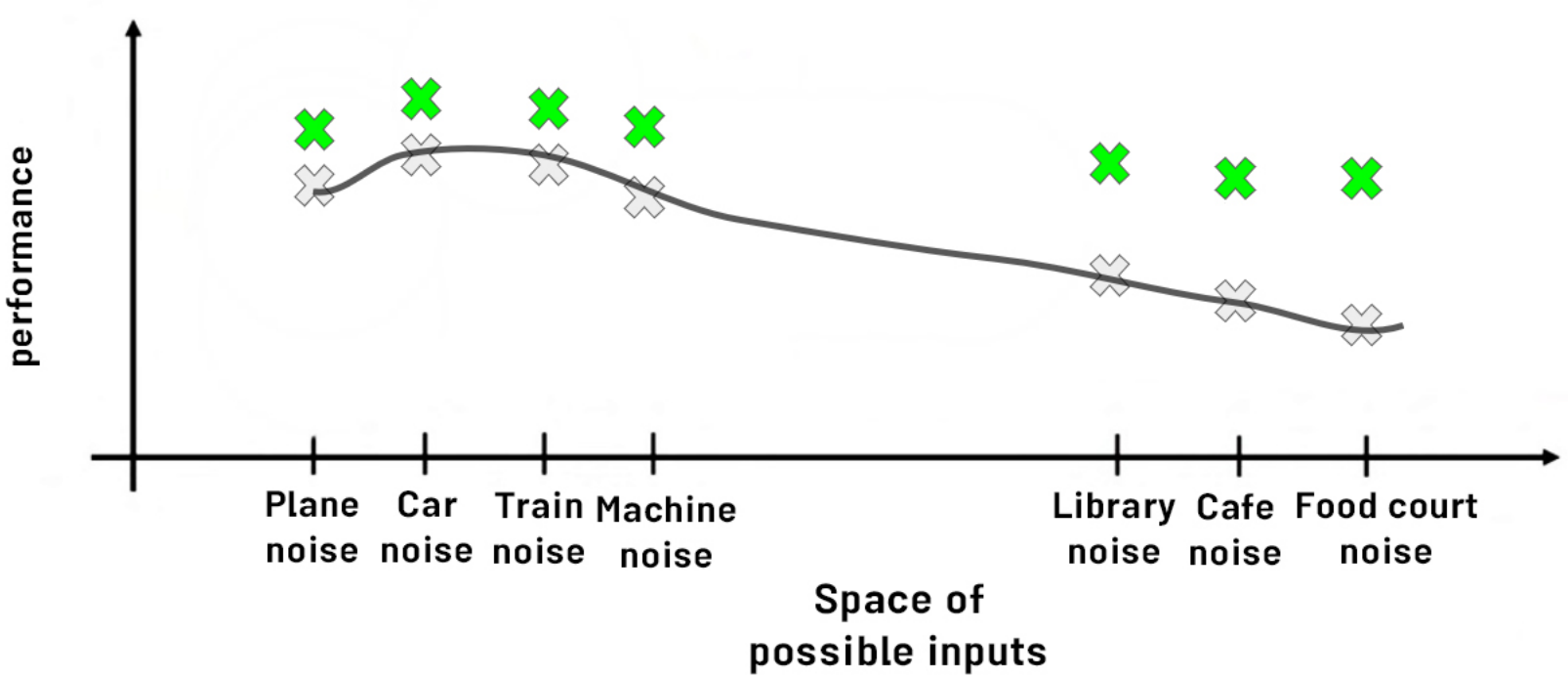

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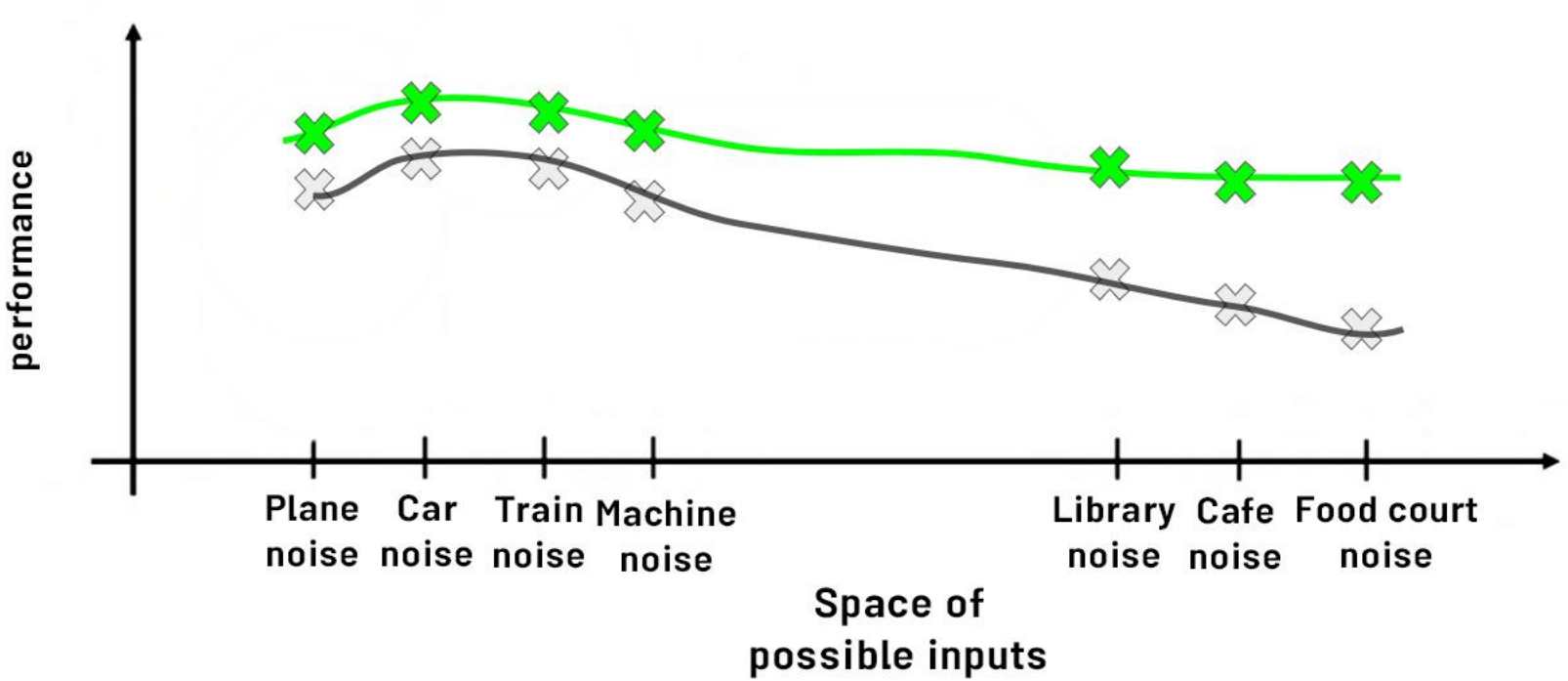

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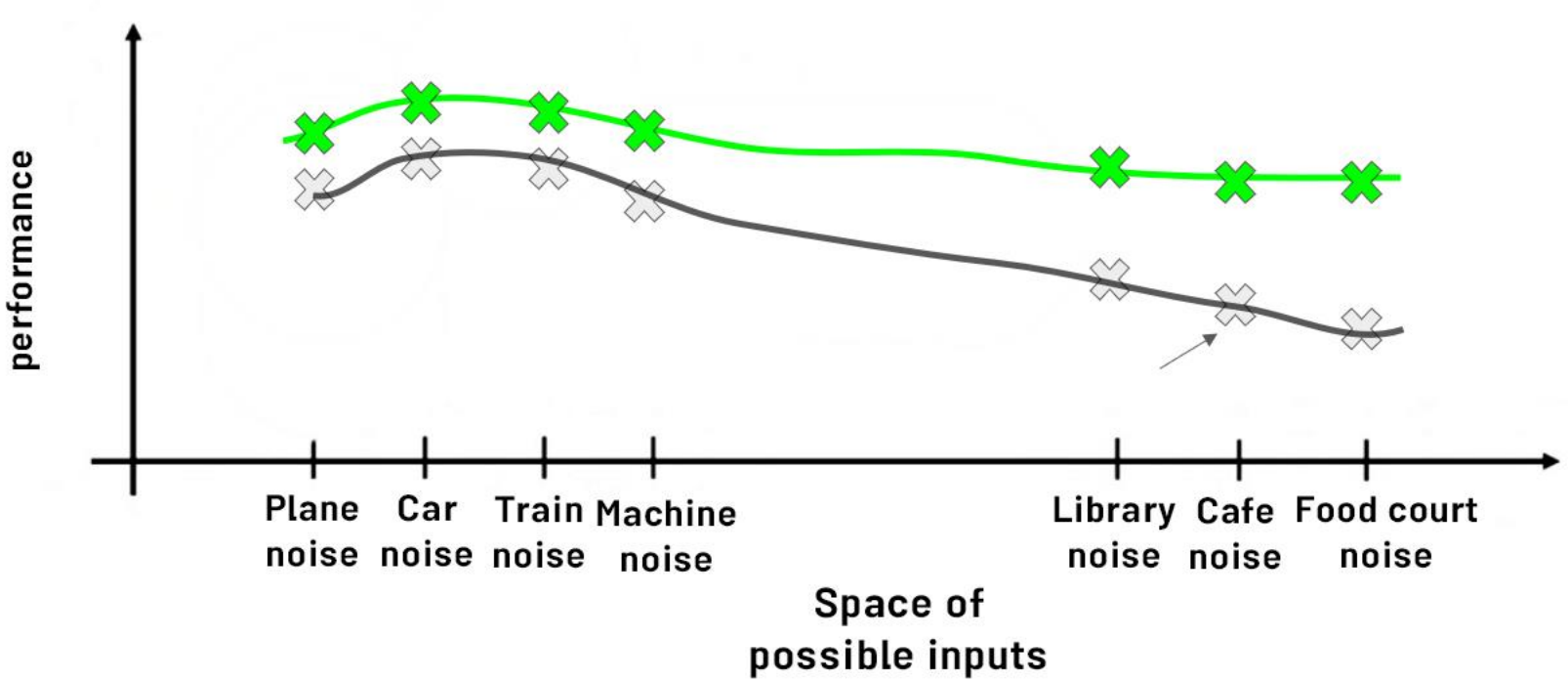

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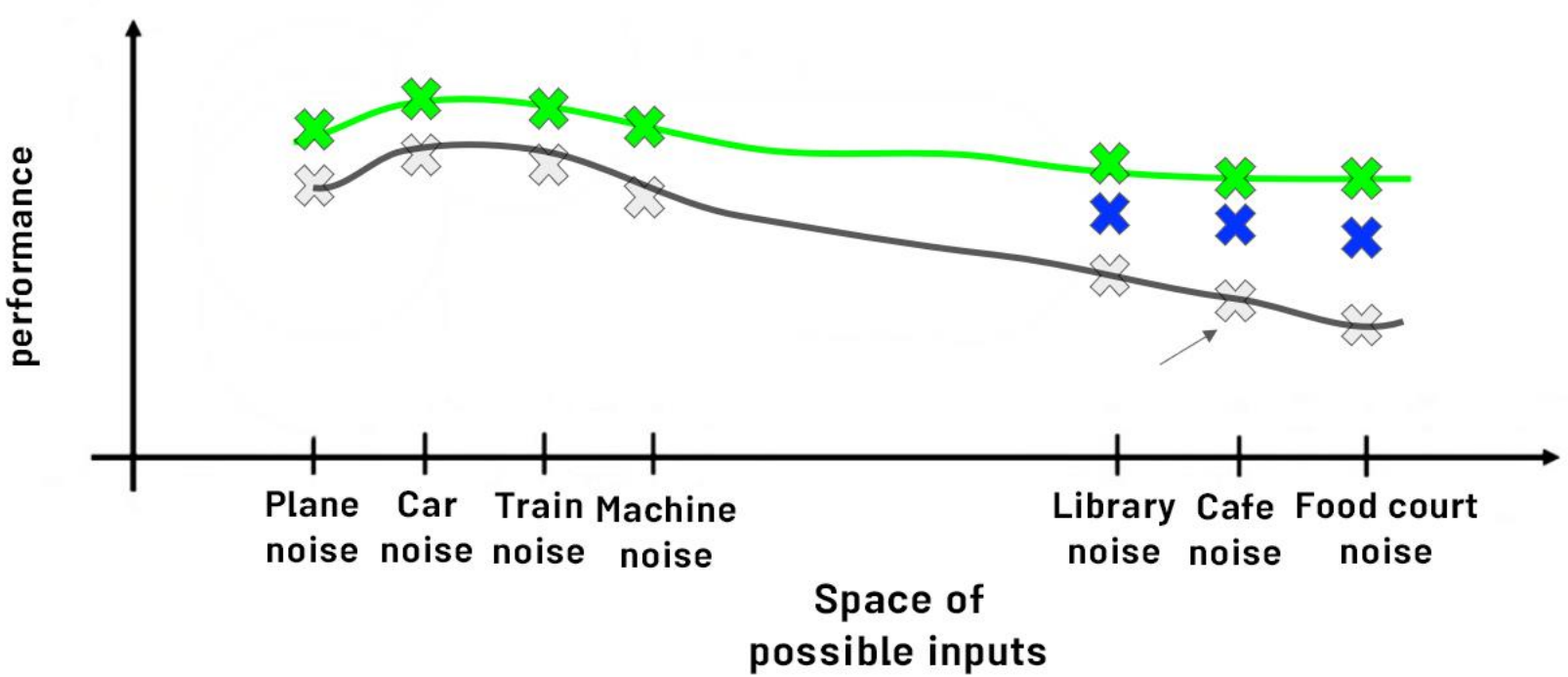

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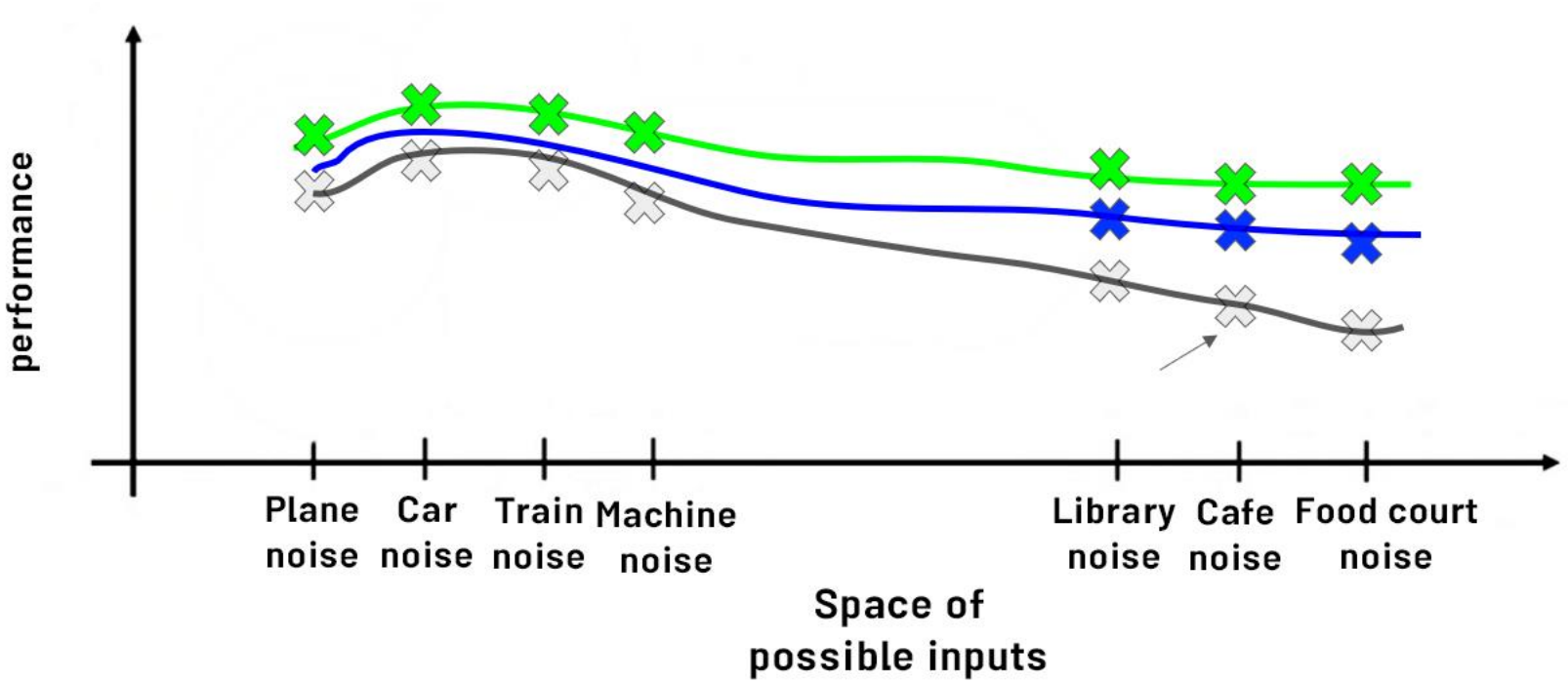

Data augmentation

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?

Data augmentation

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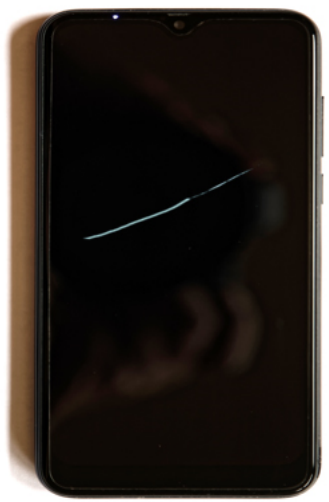
- Is the algorithm currently doing poorly on it?

Goal:

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

Image example



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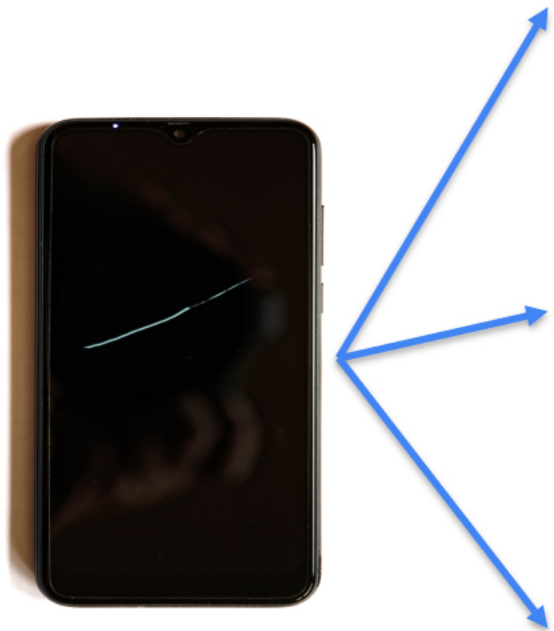

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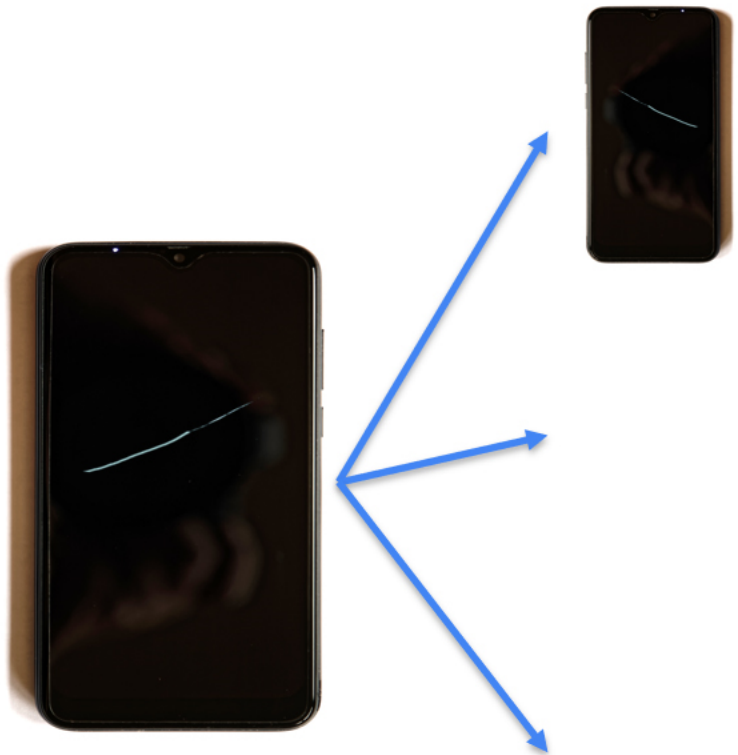

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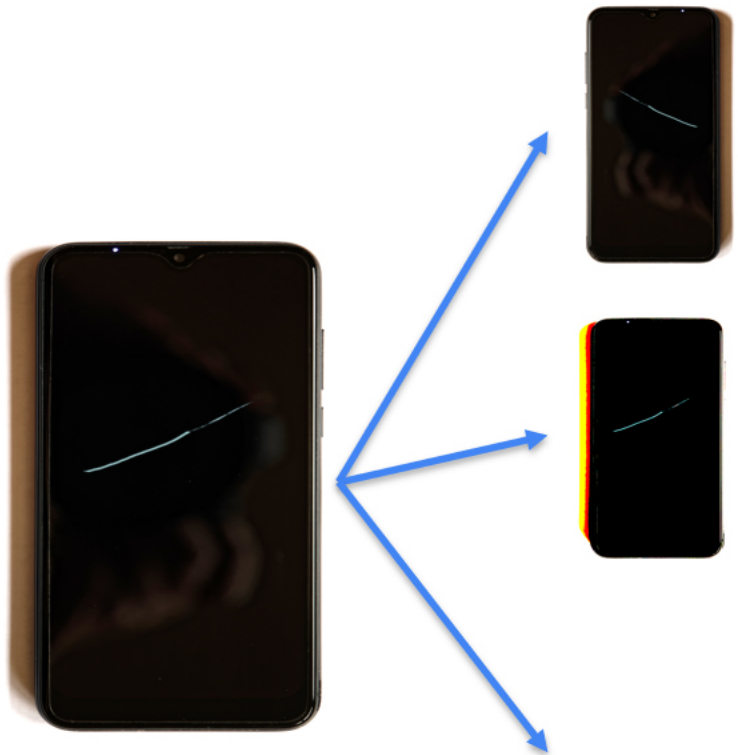

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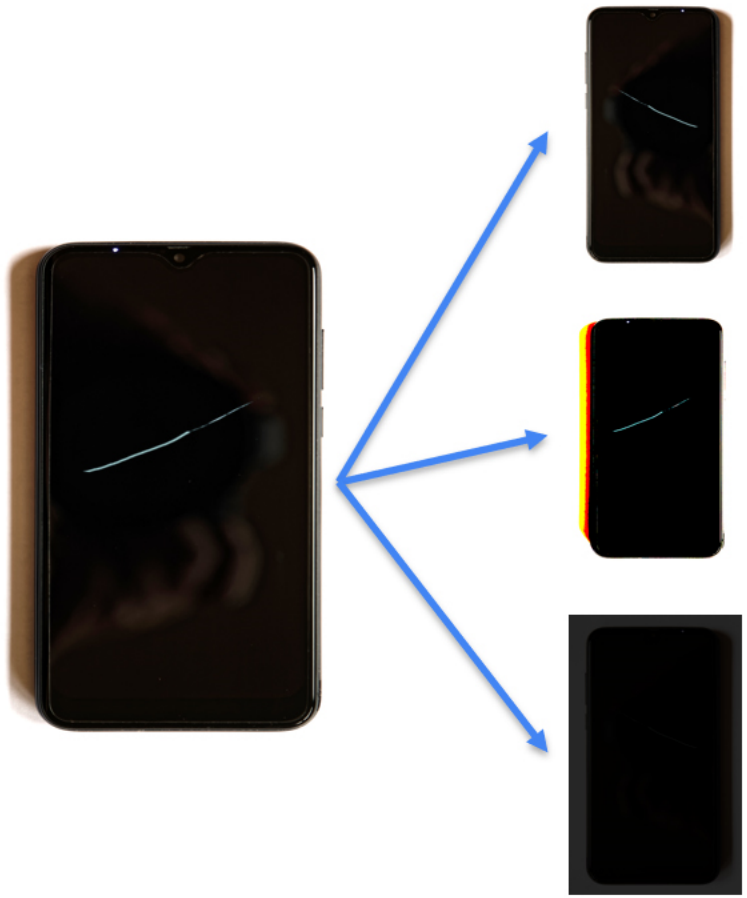

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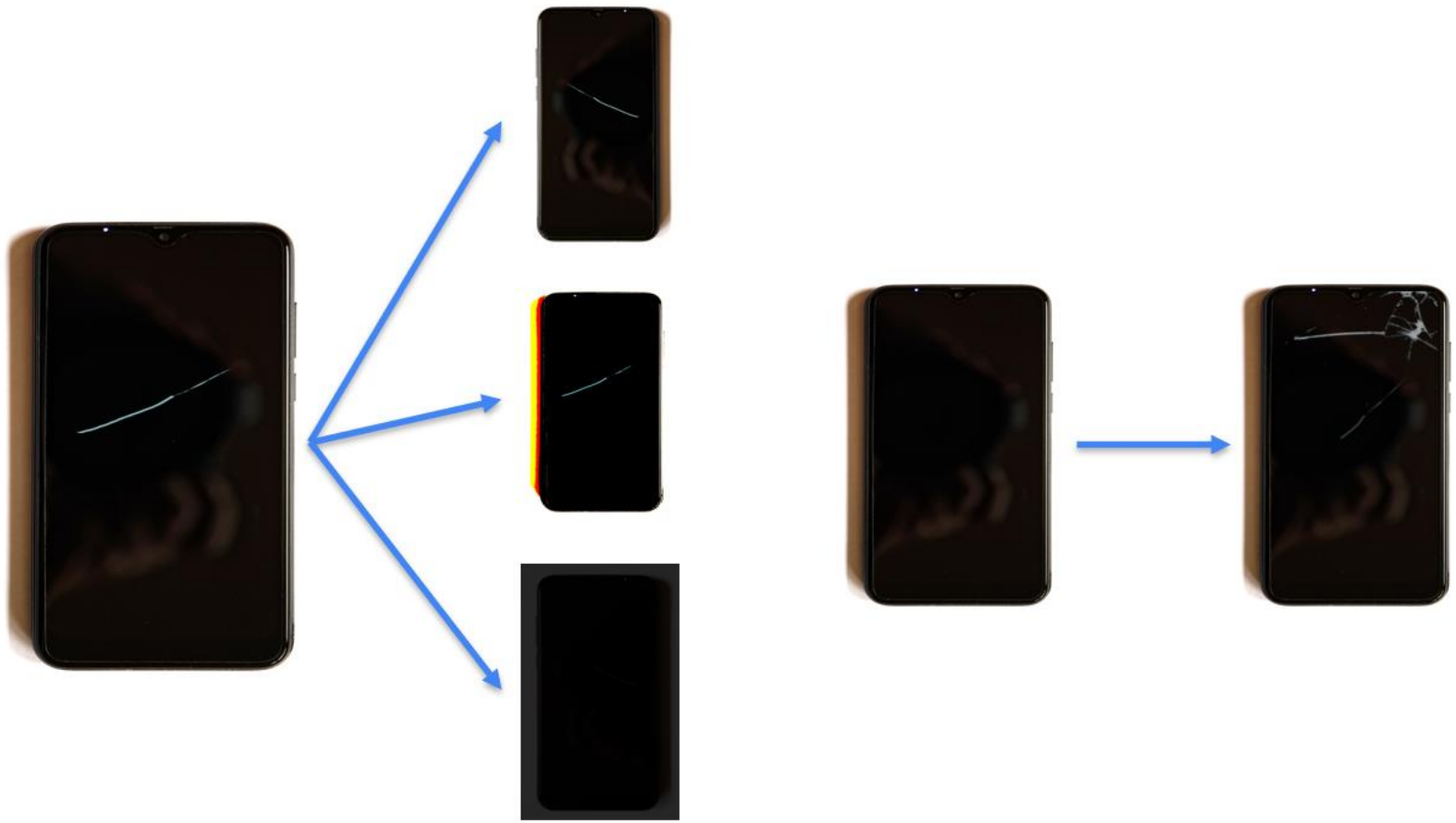


Data iteration loop

Add/improve Data

(holding model fixed)

Data iteration loop

Add/improve Data

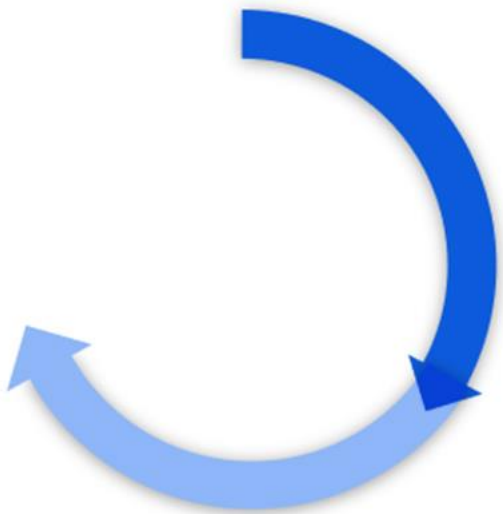
(holding model fixed)

Training

Data iteration loop

Add/improve Data

(holding model fixed)



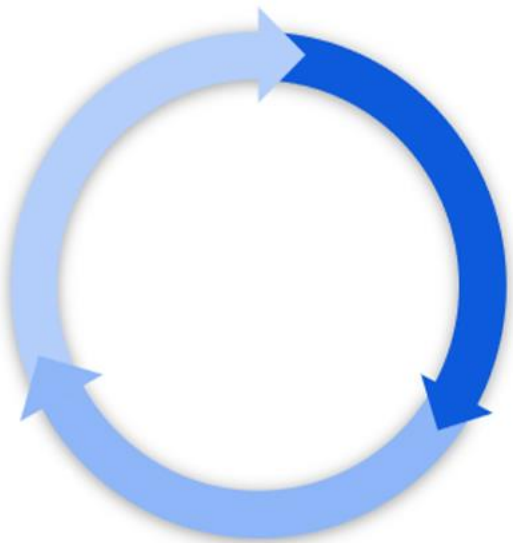
Error analysis

Training

Data iteration loop

Add/improve Data

(holding model fixed)



Error analysis

Training

Can adding data hurt performance?

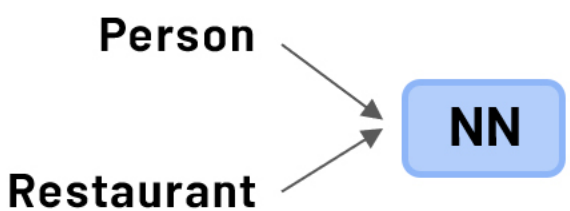
- For unstructured data problems, if:
  - The model is large (low bias).
  - The mapping X→Y is clear (e.g., humans can make accurate predictions).
- Then, adding data rarely hurts accuracy.

Corner case

?

Adding features for 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?

Other food delivery examples

- Only tea/coffee
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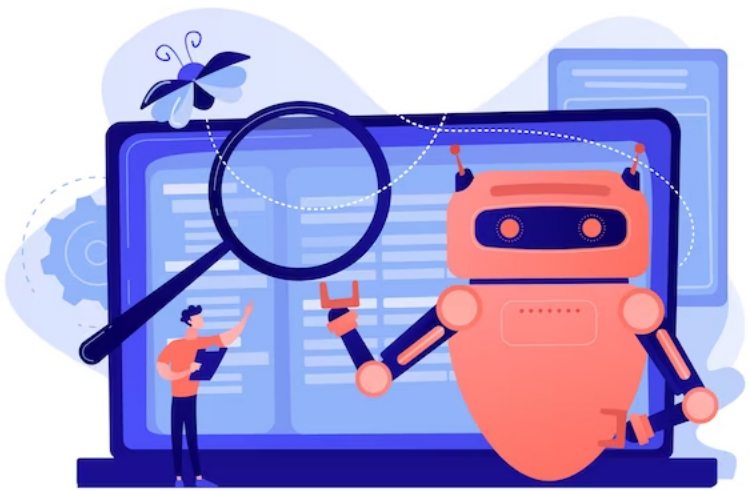
- What are the added signals (features) that can help make a decision?
- Product recommendation:
  - Collaborative filtering
  - Context based filtering



Data iteration

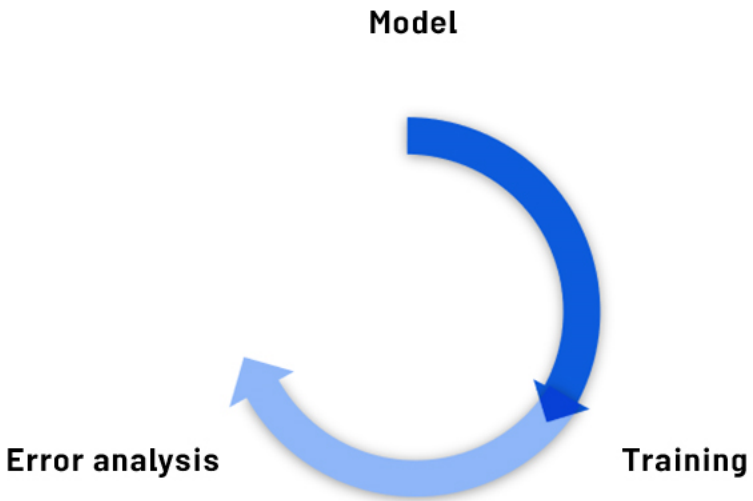
Model

Data iteration

Model

Training

Data iteration



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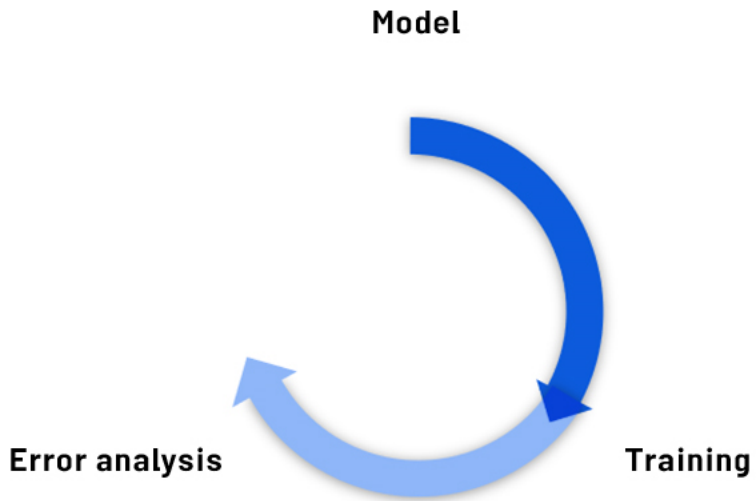
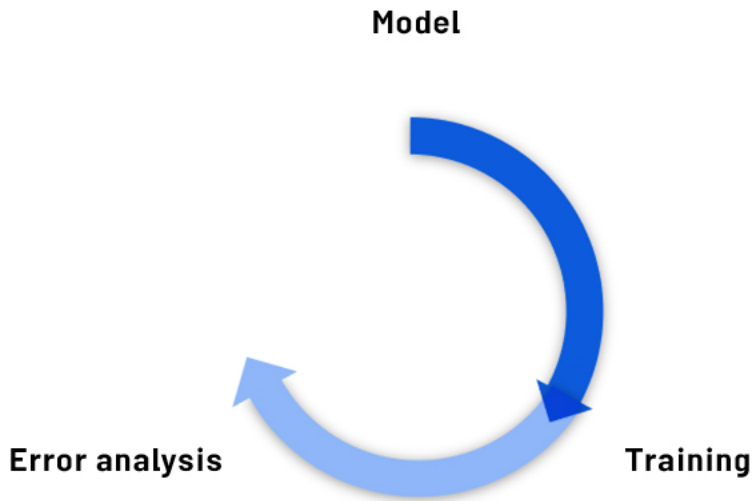


- Error analysis can be harder if there is no good baseline (such as HLP) to compare to.

Data iteration



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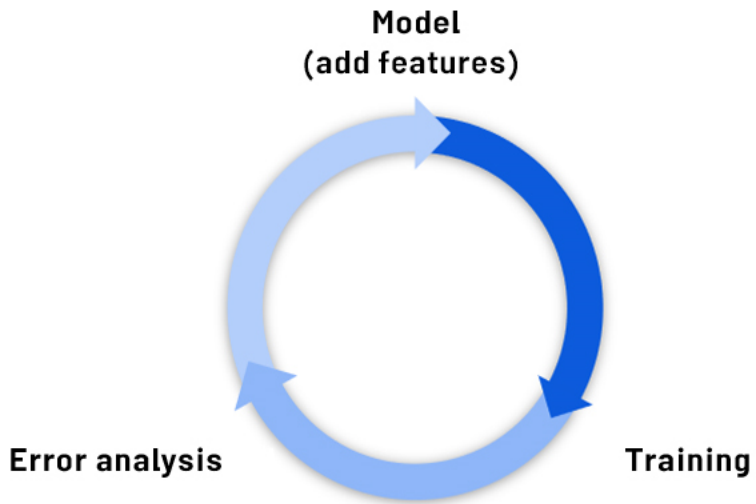
Data iteration



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Experiment tracking

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

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Desirable features

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

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