ML in Production

Part 3: Data Definition and Baseline

Ramin Toosi

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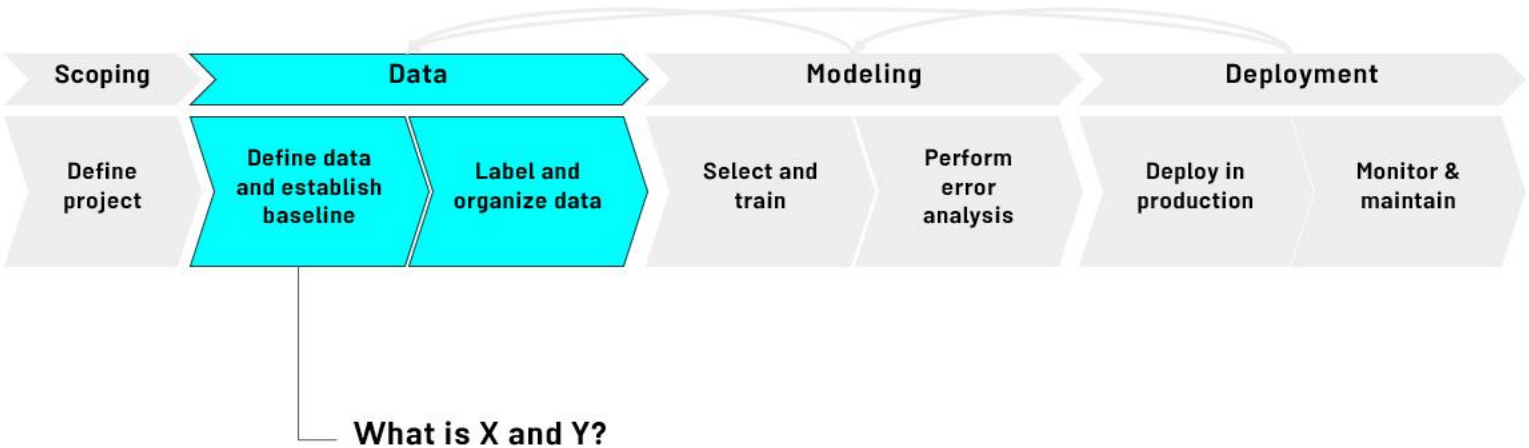
Phone defect detection

Data stage


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
What is X and Y?

User ID merge example

	Job Board (website)	Resume chat (app)
Email	ramin@avir.co.com	rtoosi@mci.ir
First Name	Ramin	Ramin
Last Name	Toosi	Tsi
Address	Vanak	?
State	Tehran	?
Zip	9393	9393

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- Bot detection?
- How a human decides?

Data definition questions

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  - 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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Data augmentation.

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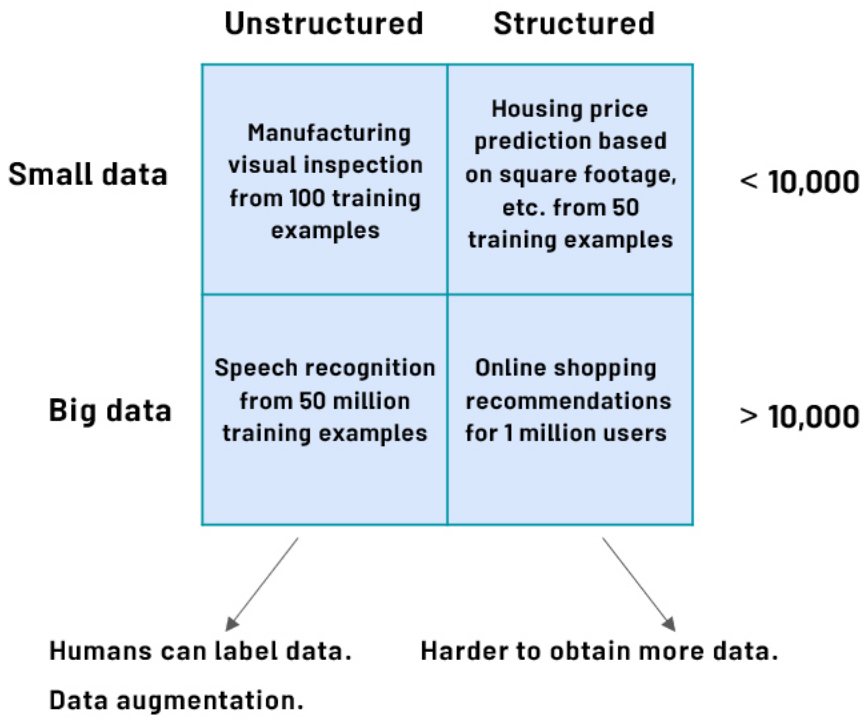

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Structured data

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

Small data vs. big data

Small data

- Clean labels are critical.
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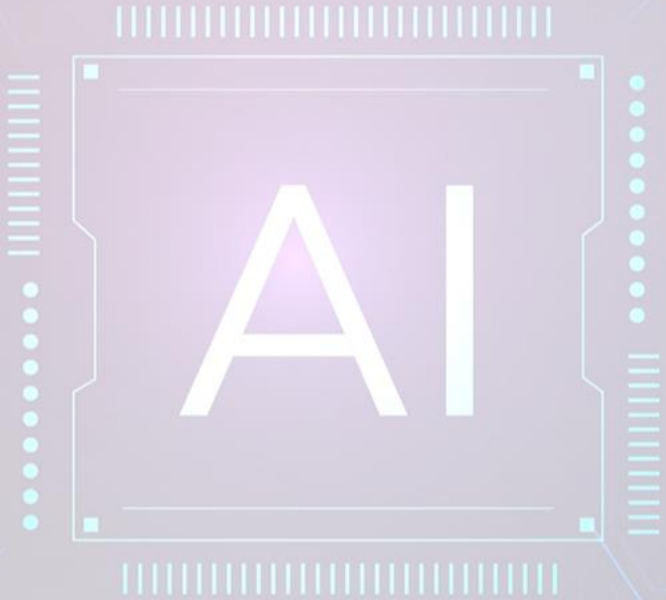
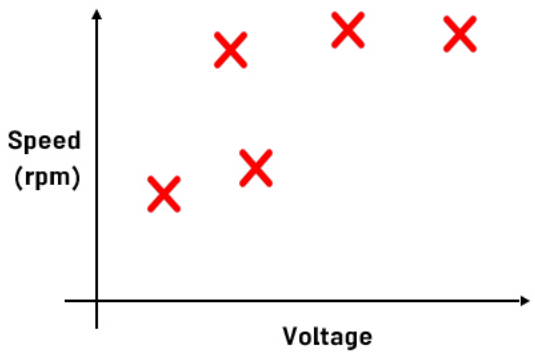
label consistency



Why label consistency is important



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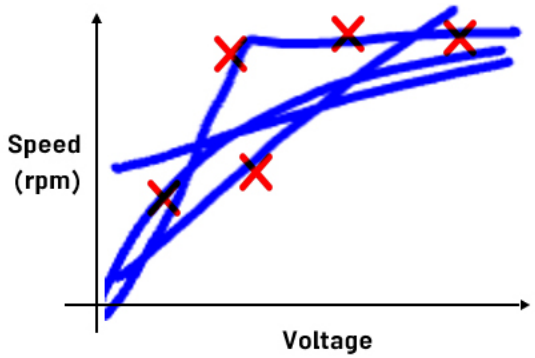

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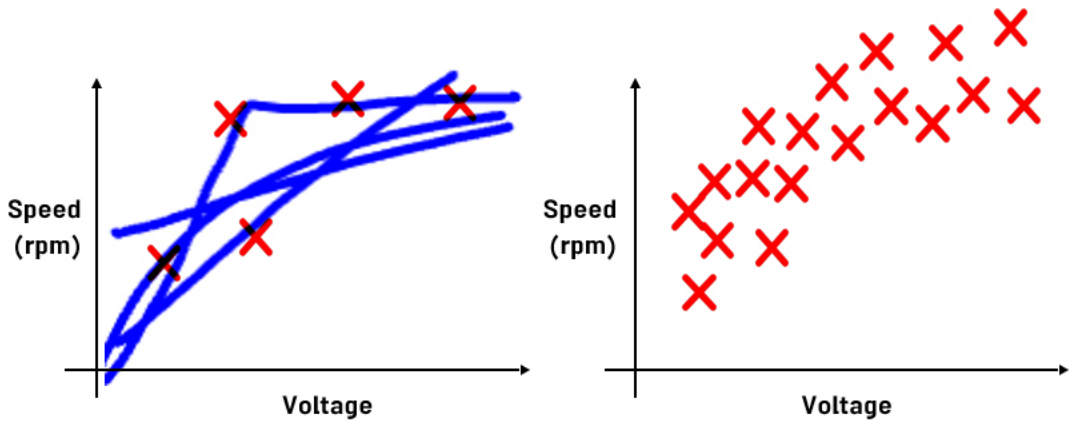

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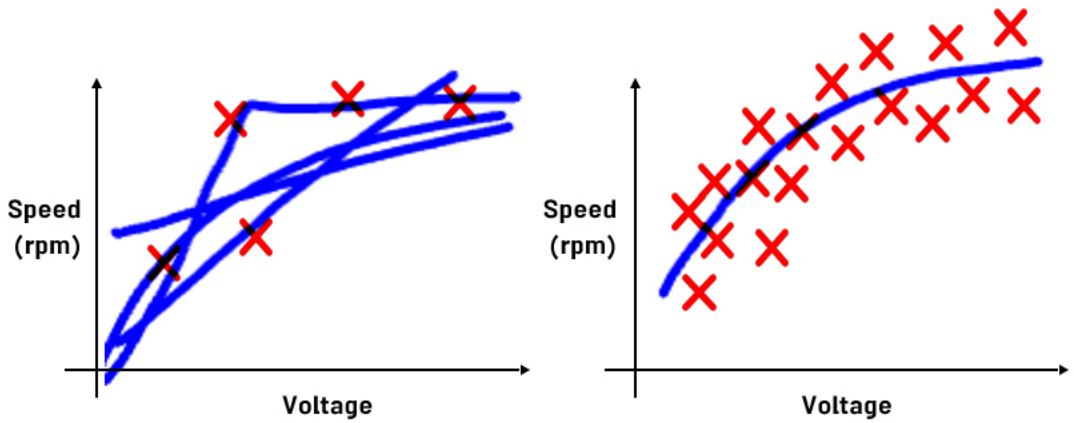

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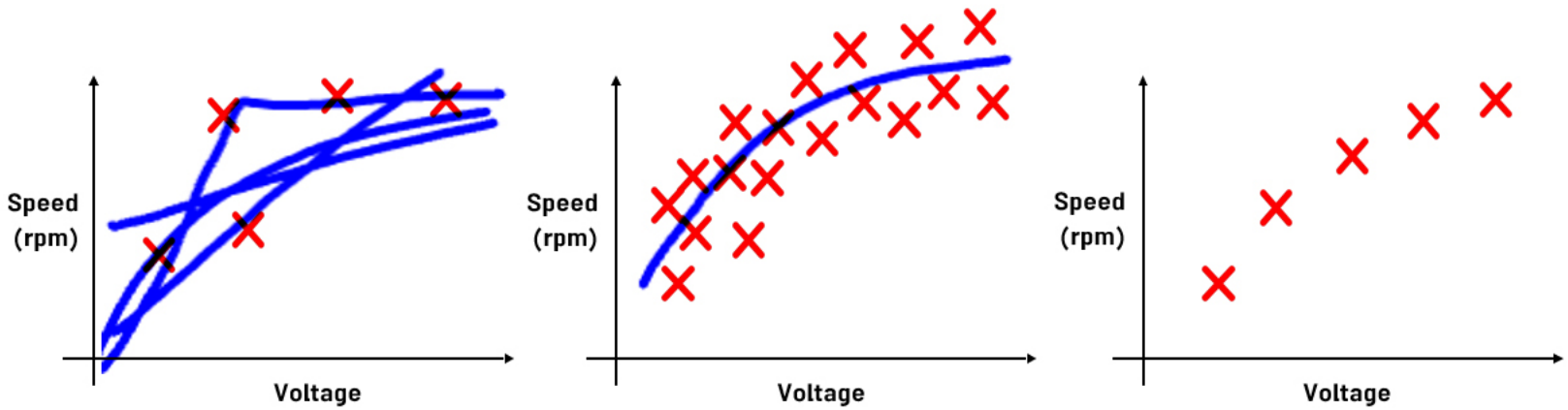

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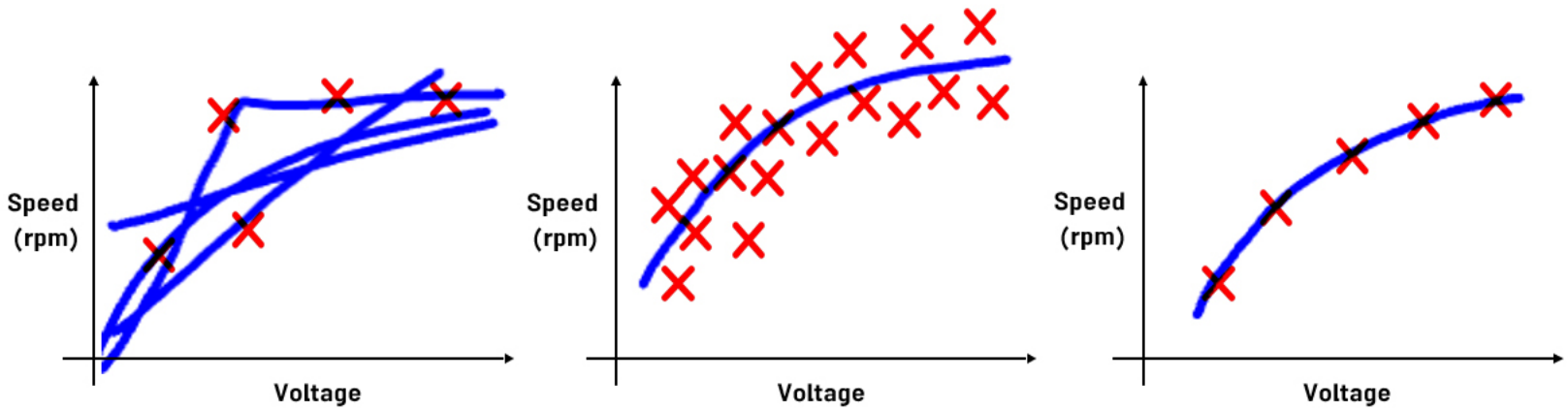

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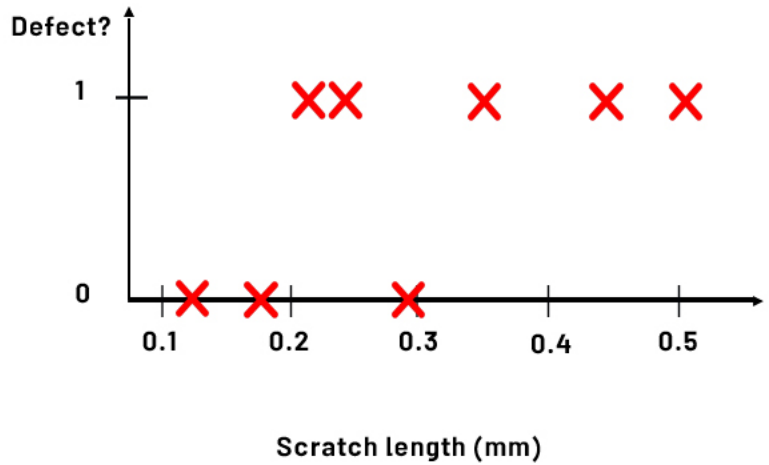

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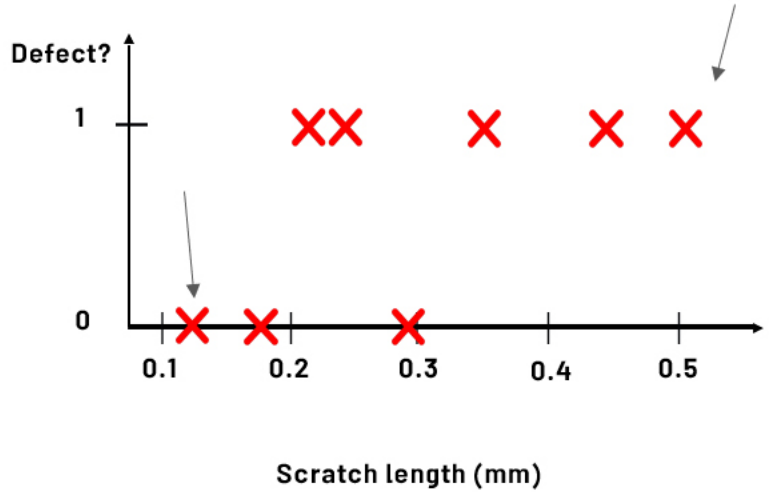

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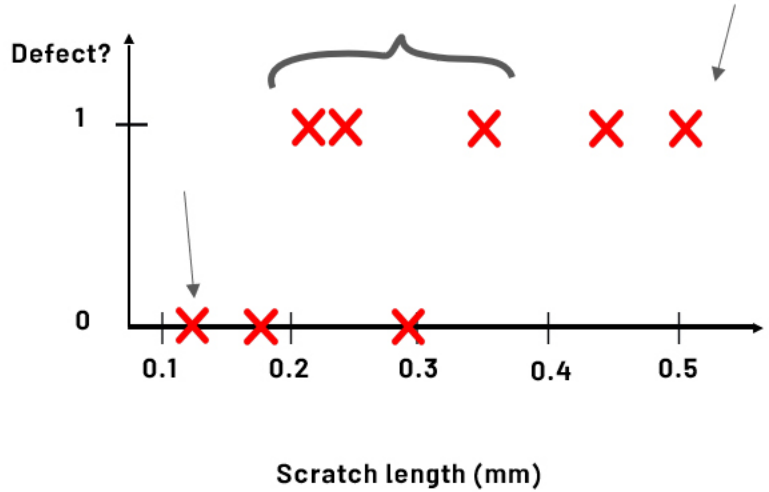

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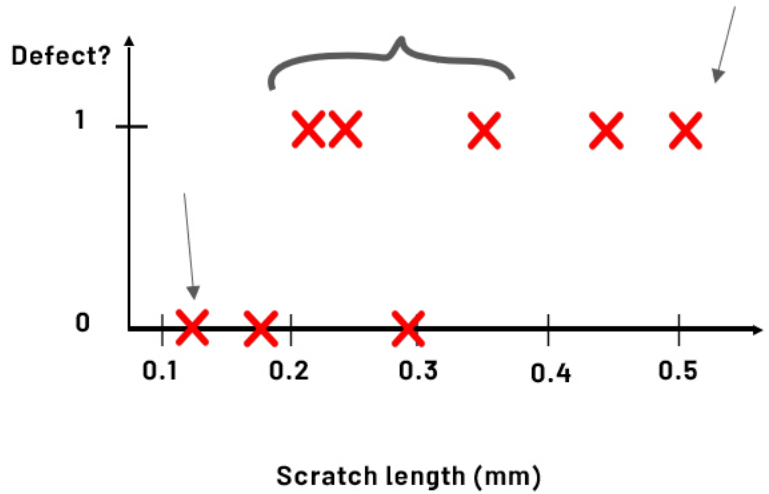

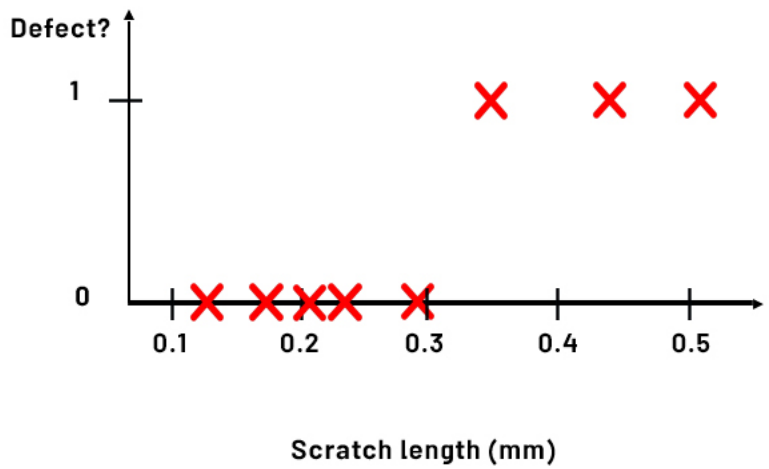

Big data problems can have small data challenges too

- 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

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

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  - "Um, nearest gas station"
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Deep scratch

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➡ Scratch

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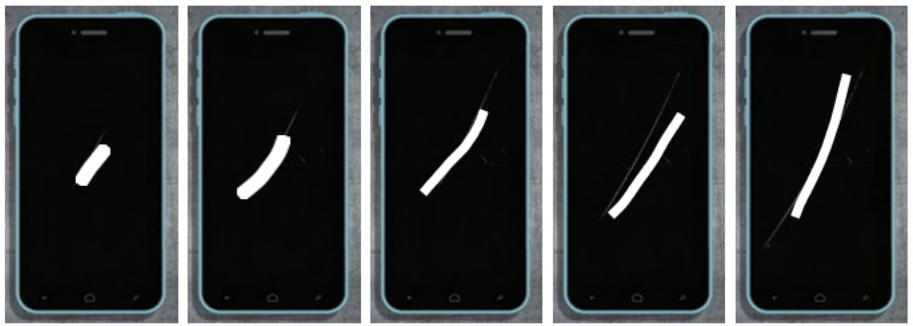

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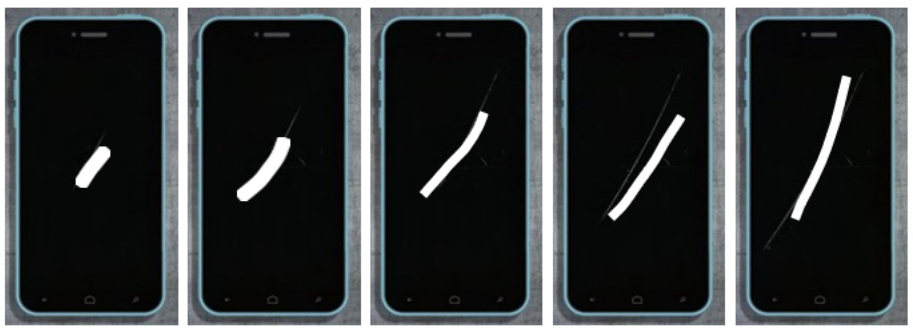

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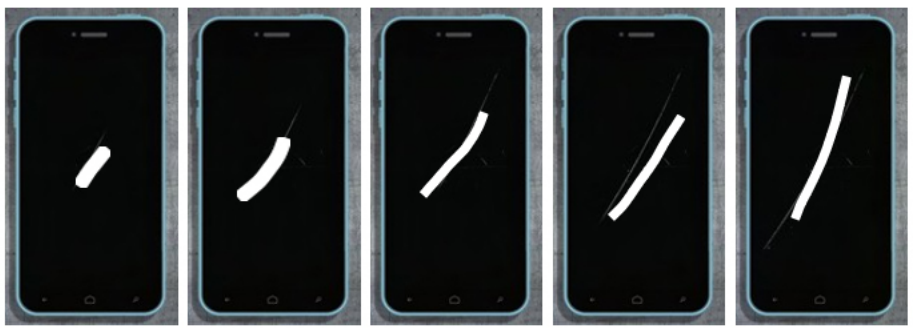

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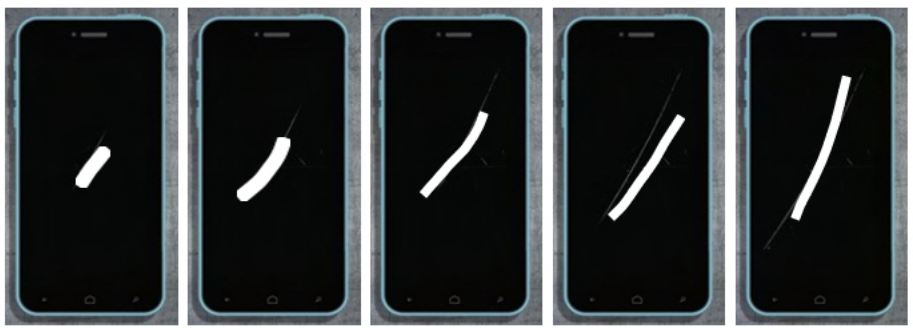

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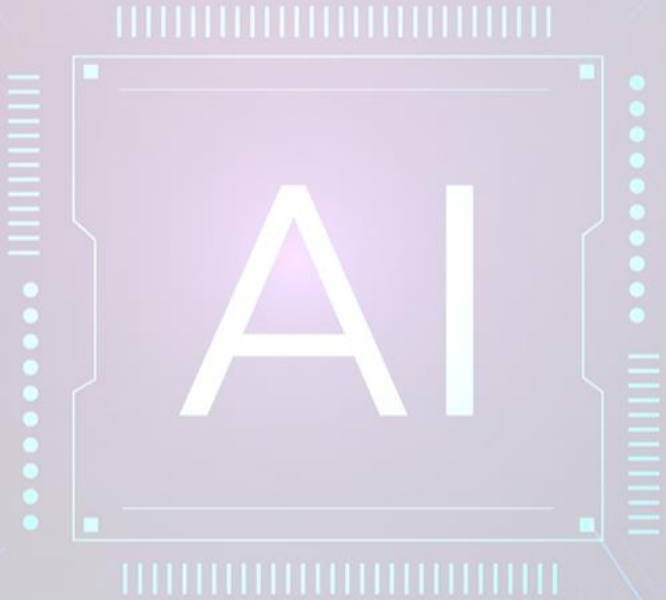
Big data

- 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.

Human Level Performance



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  - HLP is 66.7% !
  - Irreducible error or inspector agreement?

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Scratch Length	Ground Truth	Inspector
0.7	1	1
0.2	1	0
0.5	1	1
0.2	0	0
0.1	0	0
0.1	0	1

66.7%

Raising HLP

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

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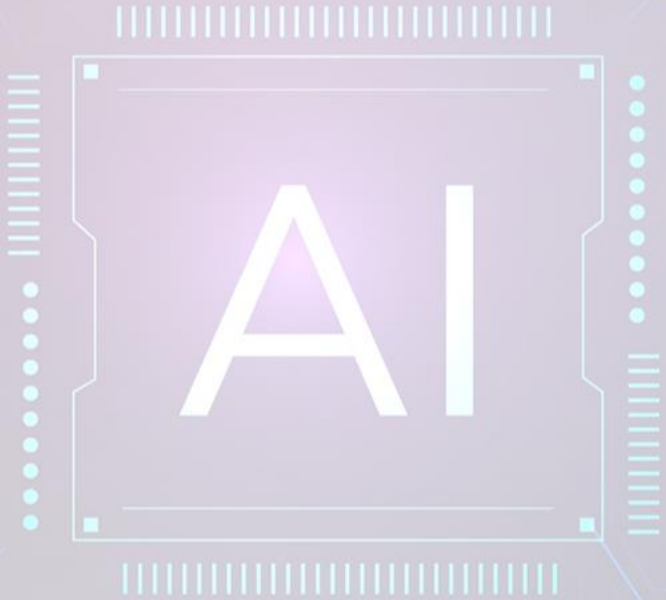
- Some exceptions:
  - User ID merging: Same person?
  - Based on network traffic, is the computer hacked?
  - Is the transaction fraudulent?
  - Spam account? Bot?
  - From GPS, what is the mode of transportation – on foot, bike, car, bus?

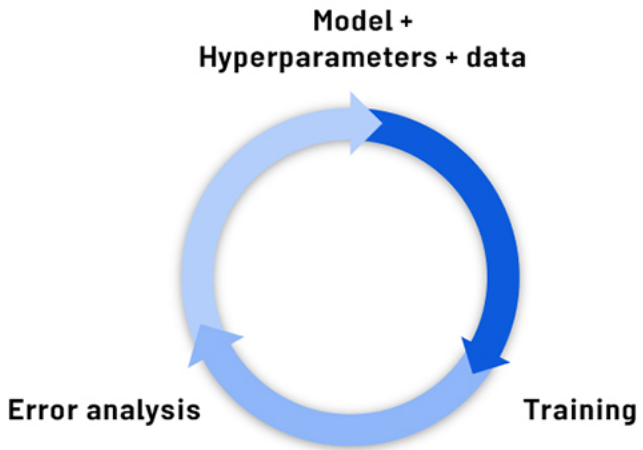
Key point on HLP

- HLP is important
- What is possible?
- HLP could be affected by labeling inconsistency
  - Cleaner data
- Improve labeling consistency

Obtaining data



How long should you spend obtaining data?



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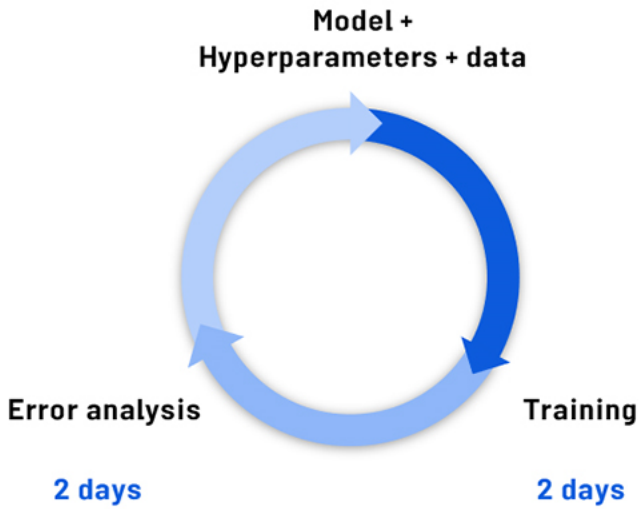

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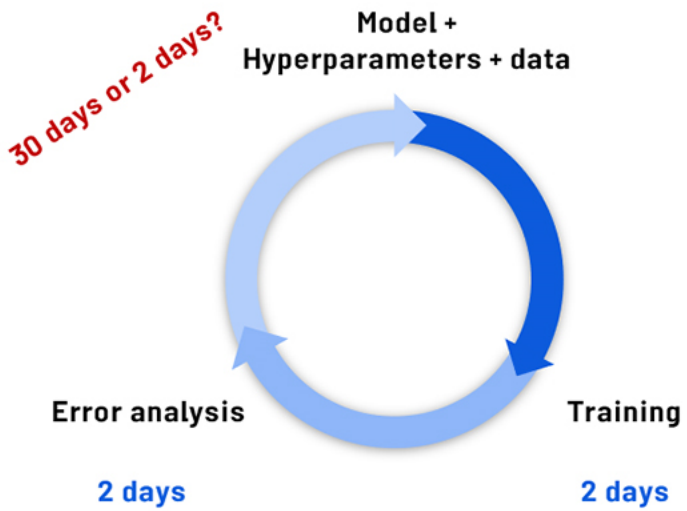

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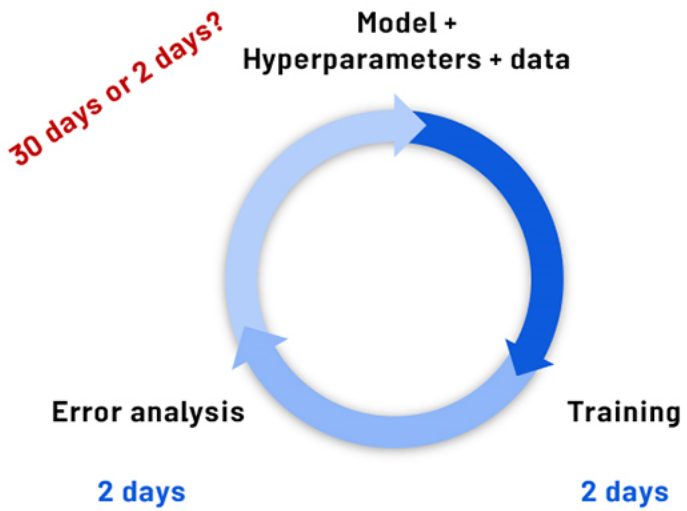

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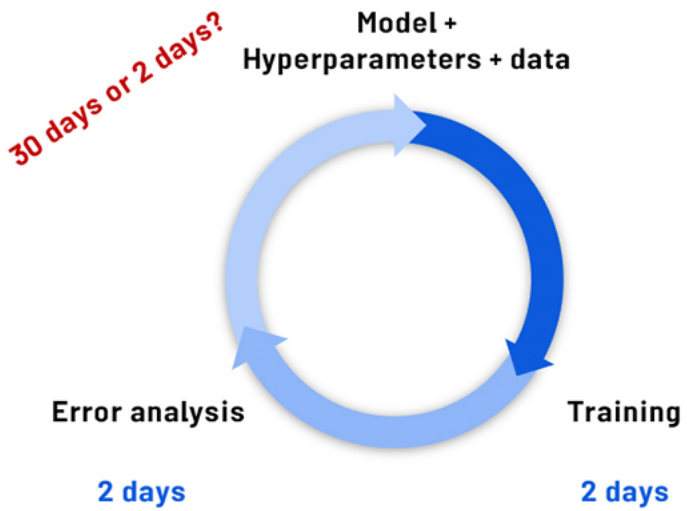

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- Instead of asking: How long it would take to obtain m examples?

  Ask: How much data can we obtain in k days.

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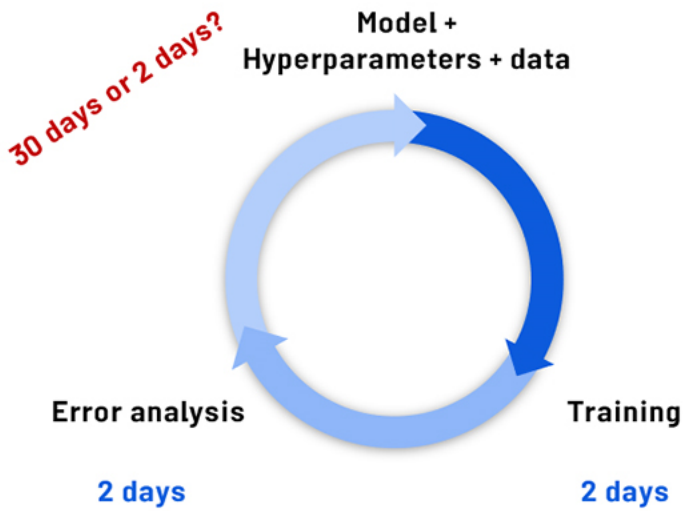

- Get into this iteration loop as quickly possible.
- Instead of asking: How long it would take to obtain m examples?

  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)

Inventory data

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Source	Amount	Cost

Inventory data

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Source	Amount	Cost
Owned		
Crowdsourced - Reading		
Pay for labels		
Purchase data		

Inventory data

- Brainstorm list of data sources ( speech recognition)

Source	Amount	Cost
Owned	100h	
Crowdsourced - Reading	1000h	
Pay for labels	100h	
Purchase data	1000h	

Inventory data

- Brainstorm list of data sources ( speech recognition)

Source	Amount	Cost
Owned	100h	0
Crowdsourced - Reading	1000h	60$
Pay for labels	100h	30$
Purchase data	1000h	50$

Inventory data

- Brainstorm list of data sources ( speech recognition)

Source	Amount	Cost
Owned	100h	0
Crowdsourced - Reading	1000h	60
Pay for labels	100h	30
Purchase data	1000h	50

Other factors: Data quality, privacy, regulatory constraints

Inventory data

- Brainstorm list of data sources ( speech recognition)

Source	Amount	Cost	Time
Owned	100h	0	0
Crowdsourced - Reading	1000h	60	14 days
Pay for labels	100h	30	8 days
Purchase data	1000h	50	1 day

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

Data pipeline

	Job Board (website)	Resume chat (app)
Email	ramin@avir.co.com	rtoosi@mci.ir
First Name	Ramin	Ramin
Last Name	Toosi	Tsi
Address	Vanak	?
State	Tehran	?
Zip	9393	9393

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Data cleaning

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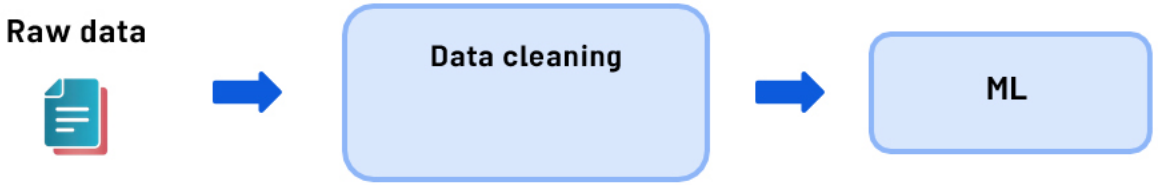

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Data pipeline

Development

Data

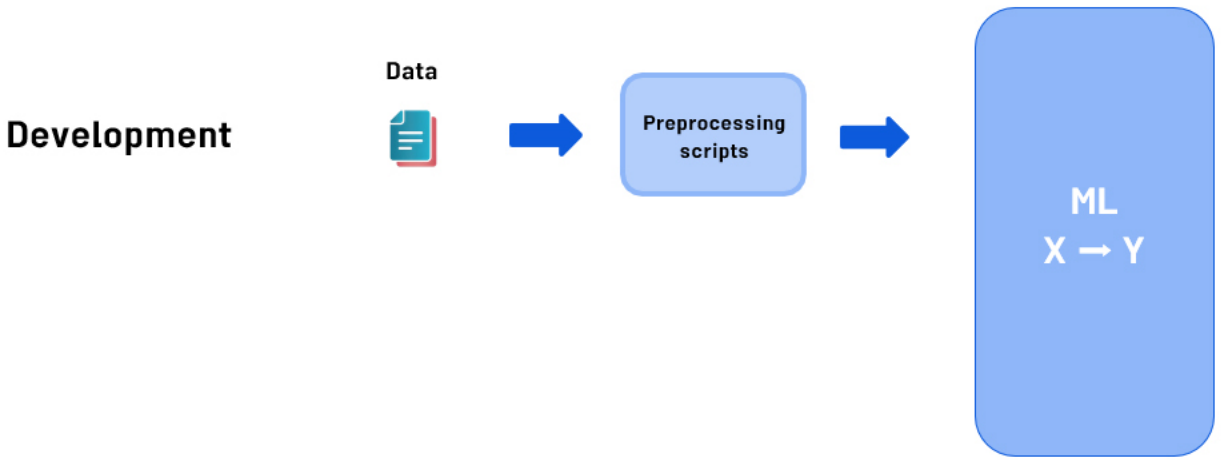
Data pipeline

Development

Data

Preprocessing scripts

Data pipeline



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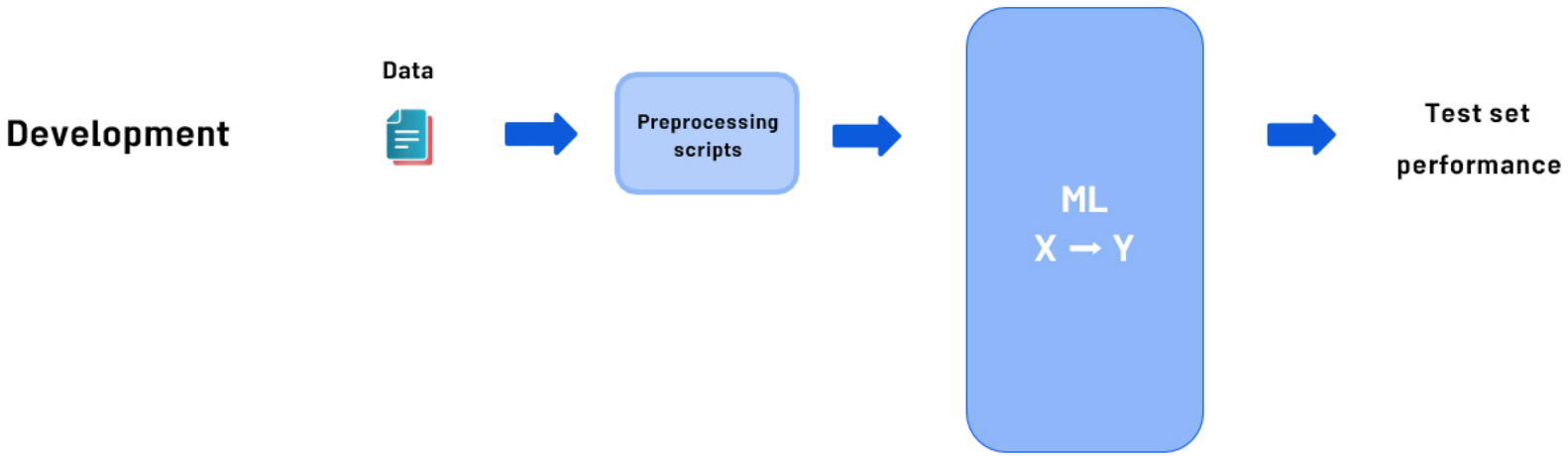

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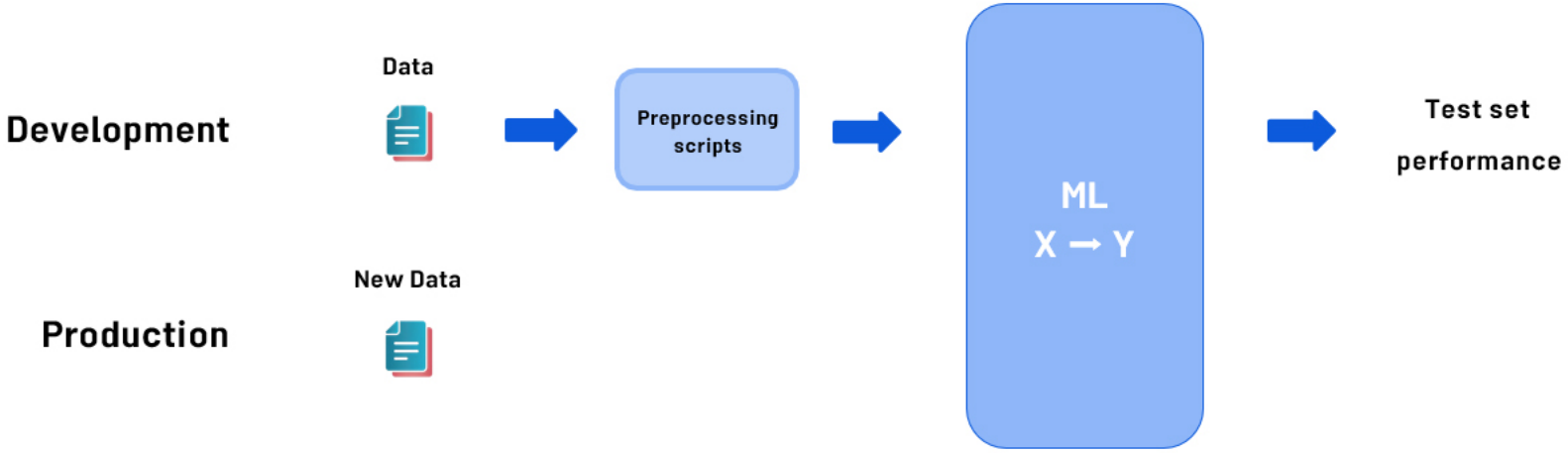

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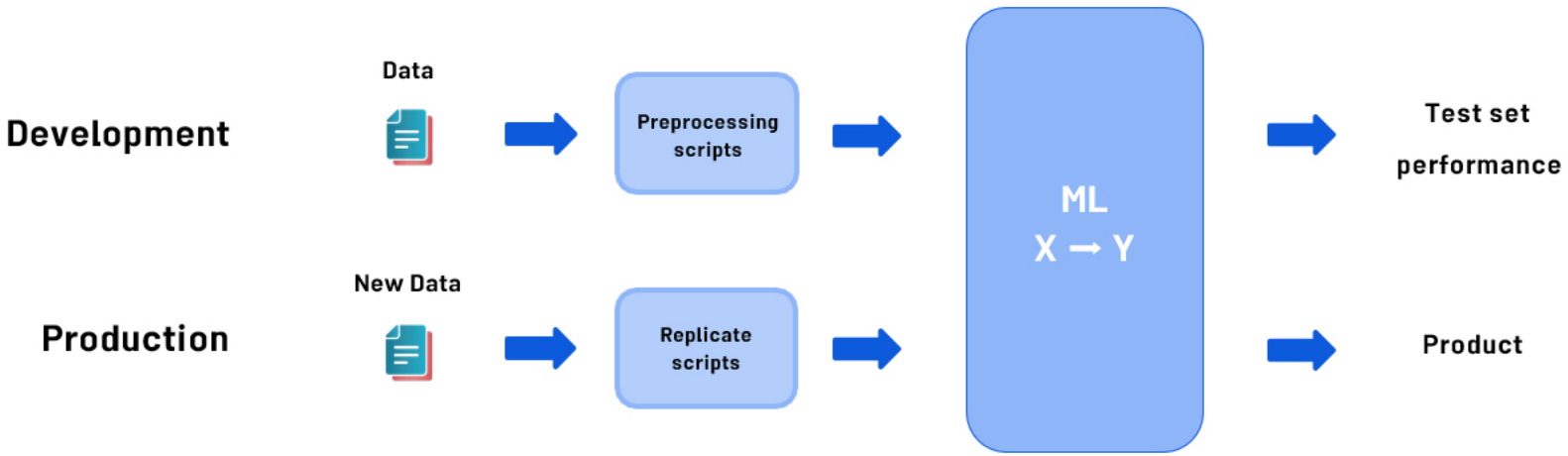

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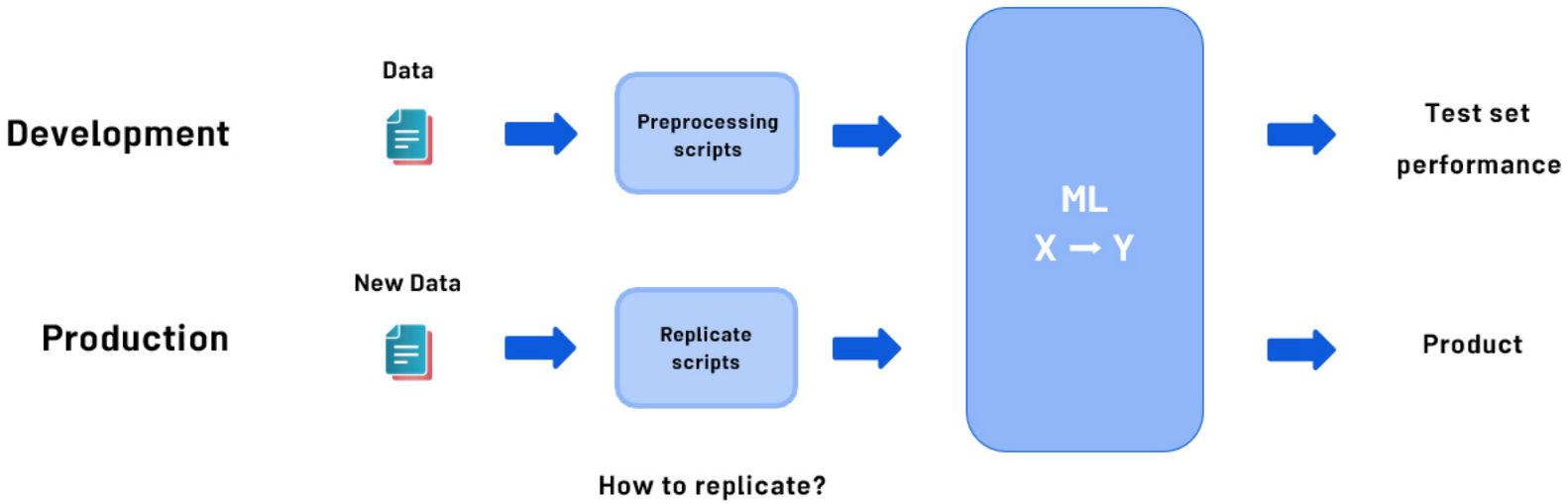

POC and Production phases

- **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.

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  - 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,...

A more complex data pipeline example

- Task: Predict if someone is looking for a job.

  (x = user data, y = looking for a job?)

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ML Code

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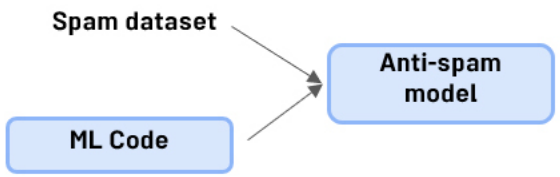

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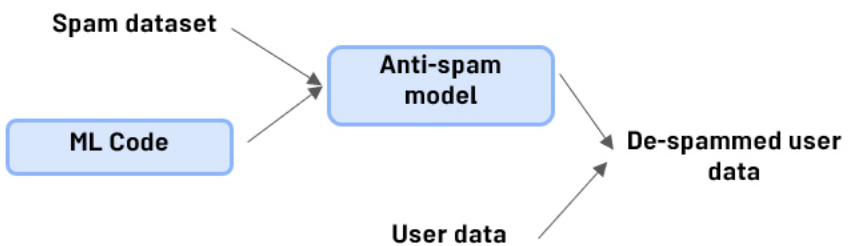

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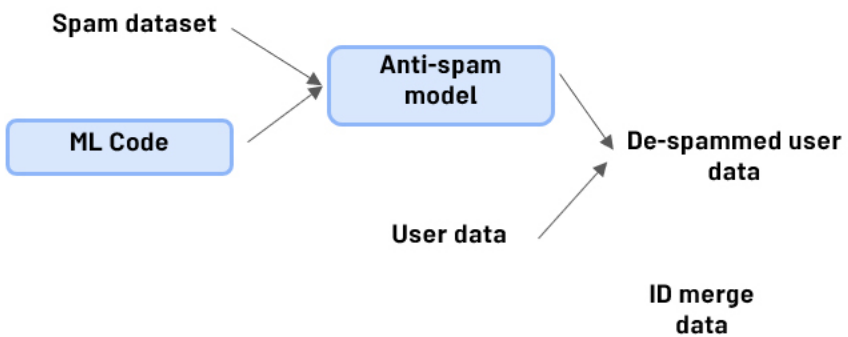

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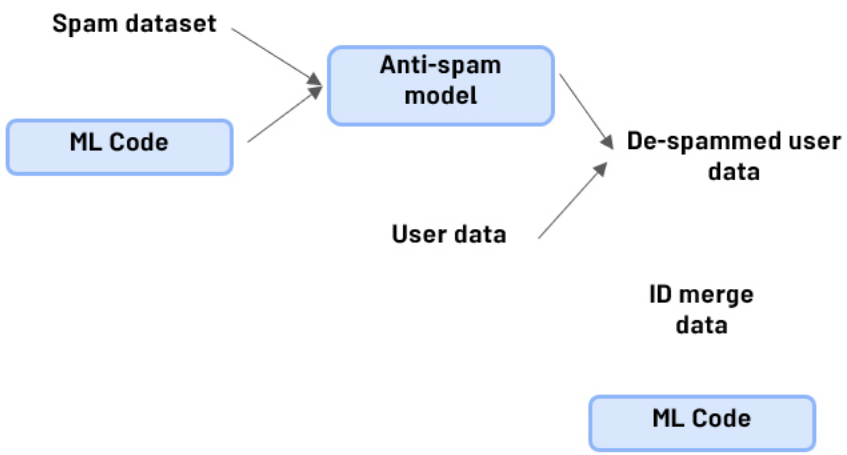

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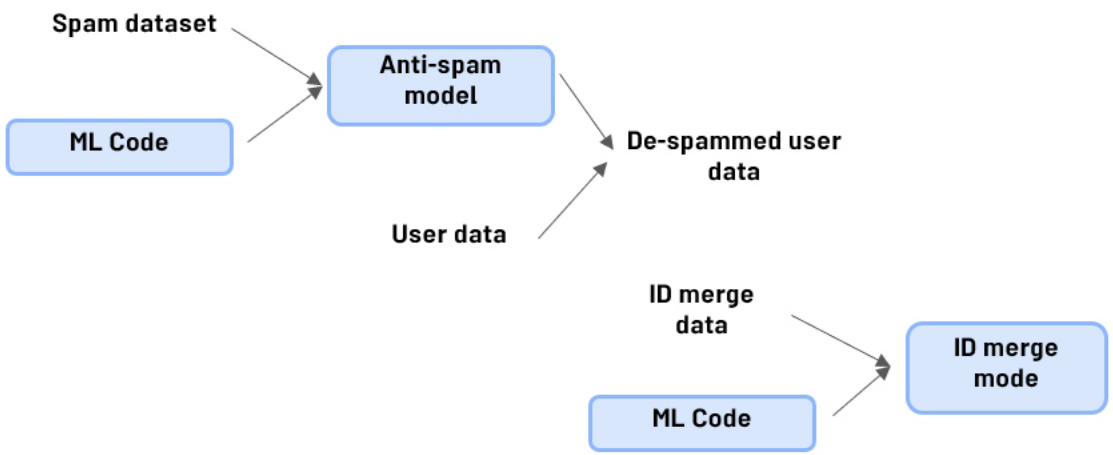

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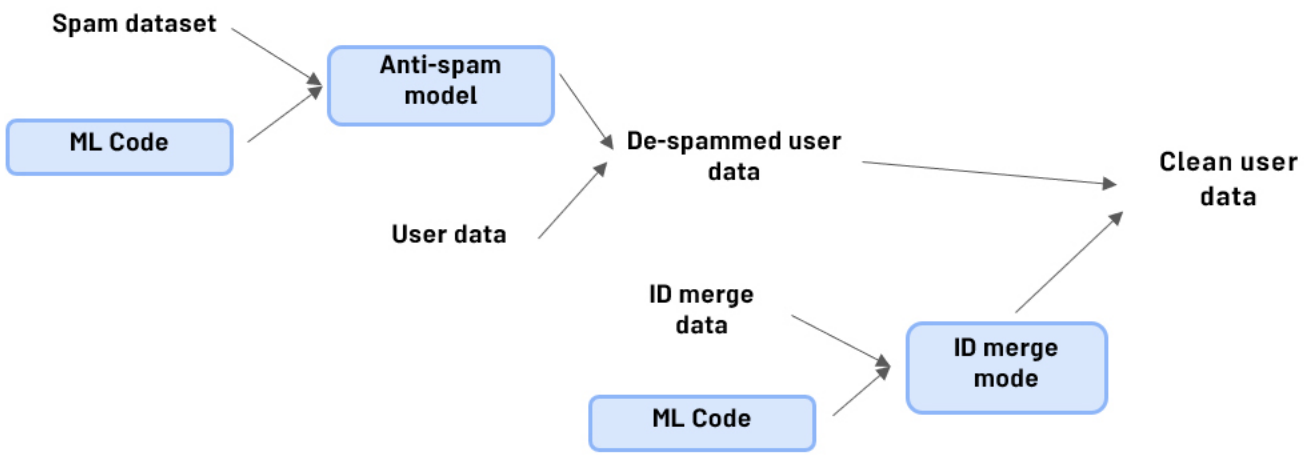

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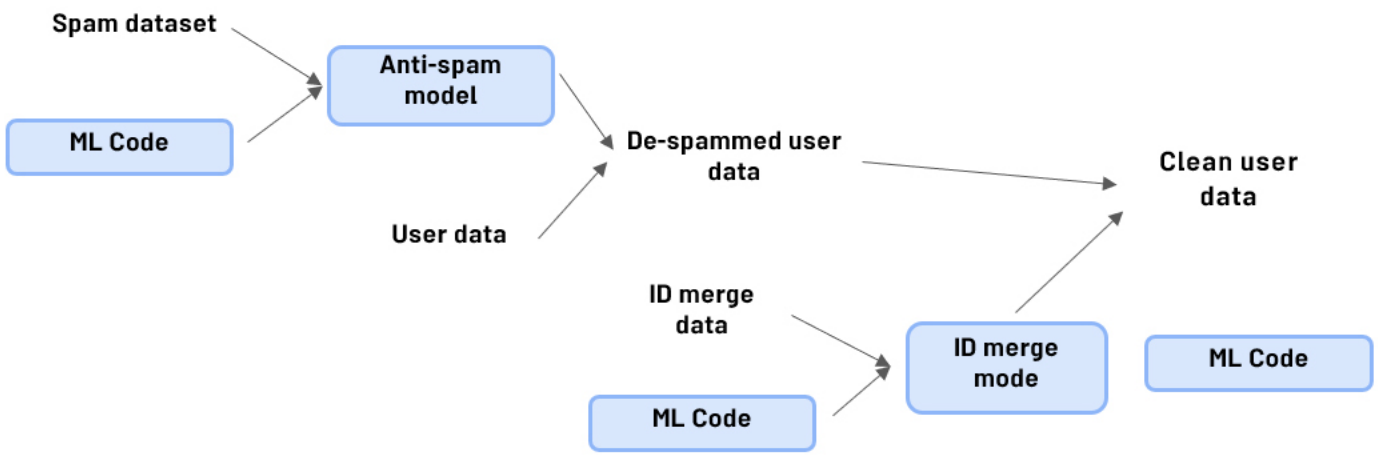

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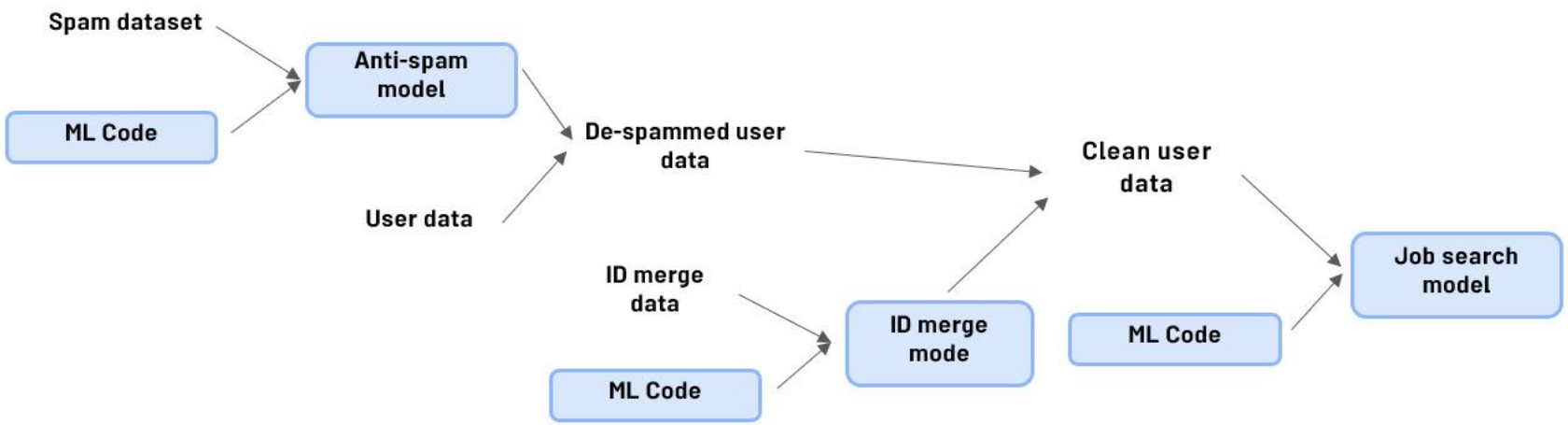

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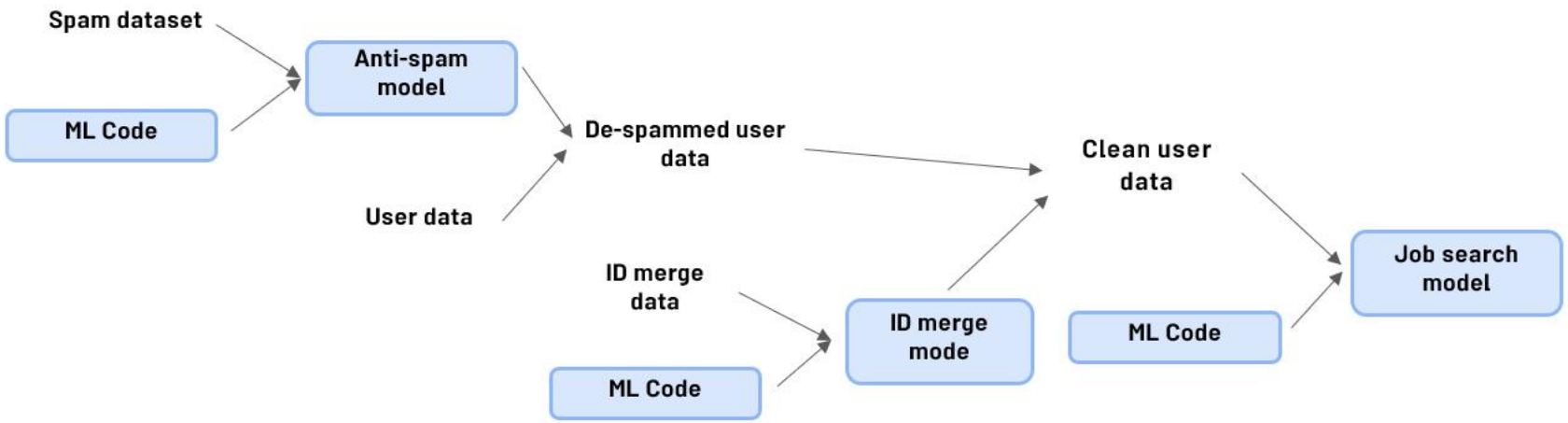

Keep track of data provenance and lineage

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,....

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.

Balanced train/dev/test splits in small data problems

- Visual inspection example: 100 examples, 30 positive (defective)
  - Train/dev/test:
  - Random split:
  - Want:
- No need to worry about this with large datasets – a random split will be representative.

Balanced train/dev/test splits in small data problems

- Visual inspection example: 100 examples, 30 positive (defective)
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  - Train/dev/test: 60% / 20% / 20%
  - Random split: 21 / 2 / 7 35% / 10% / 35% Positive examples
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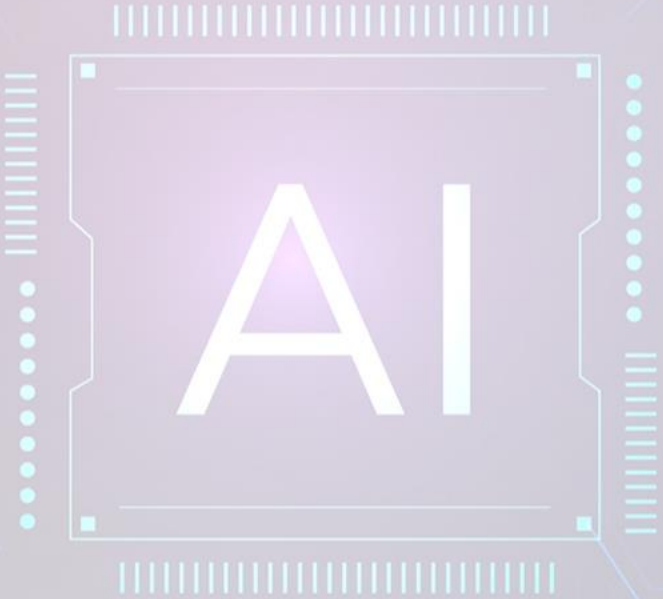
- Visual inspection example: 100 examples, 30 positive (defective)
  - Train/dev/test: 60% / 20% / 20%
  - Random split: 21 / 2 / 7 35% / 10% / 35% Positive examples
  - Want: 18 / 6 / 6 30% / 30% / 30%
- No need to worry about this with large datasets – a random split will be representative.

Scoping



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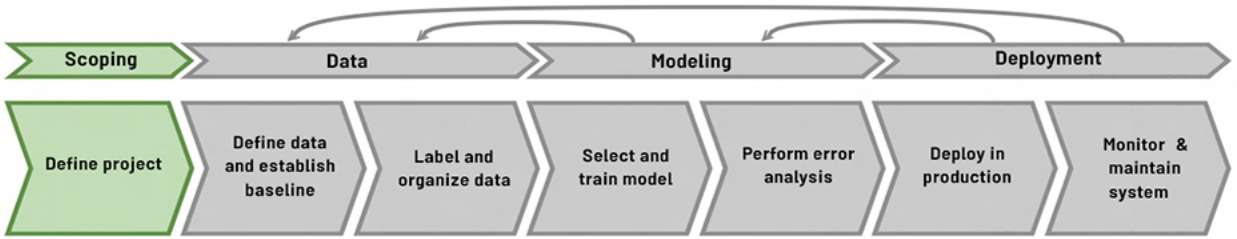

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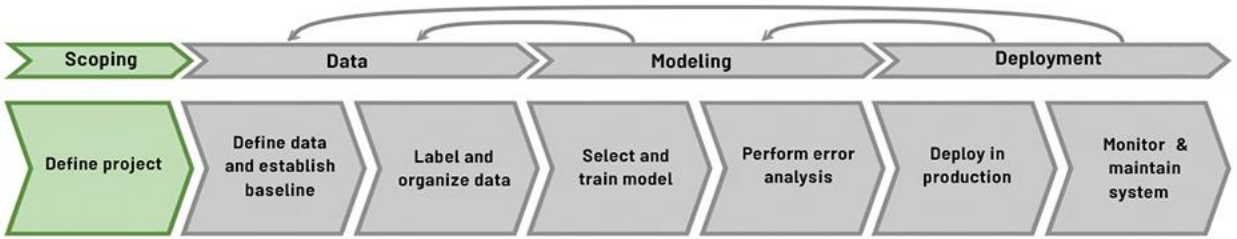
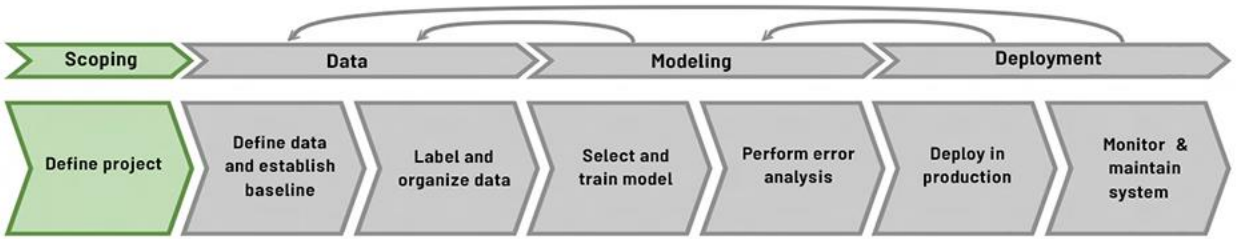


- Ecommerce retailer looking to increase sales

Scoping example



- Ecommerce retailer looking to increase sales
  - Better recommender system
  - Better search
  - Improve catalog data
  - Inventory management
  - Price optimization

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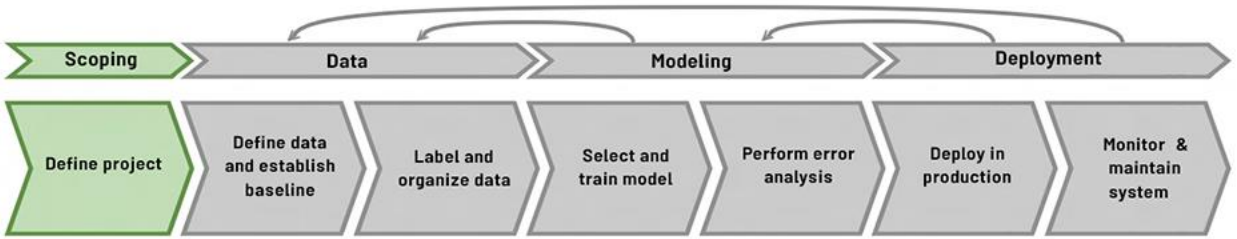

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- **Questions**
  - What projects should we work on?
  - What are the metrics for success?
  - What are the resources (data, time,people) needed?

Scoping process

Identify a business problem
(not an AI problem)

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- **What are the top 3 things you wish were working better?**
  - Increase conversion
  - Reduce inventory
  - Increase margin (profit per item)

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⬇

Brainstorm AI solutions

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Scoping process

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Separating problem identification from solution

Problem	Solution

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Increase conversion	Search, recommendations

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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

Feasibility: Is this project technically feasible?

- Use external benchmark (literature, other company, competitor)

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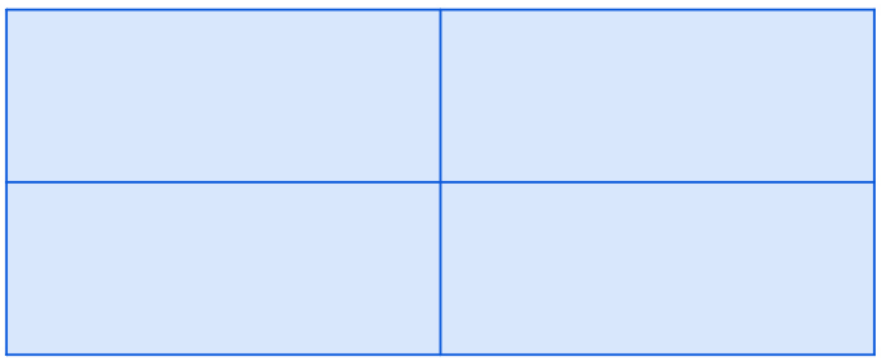

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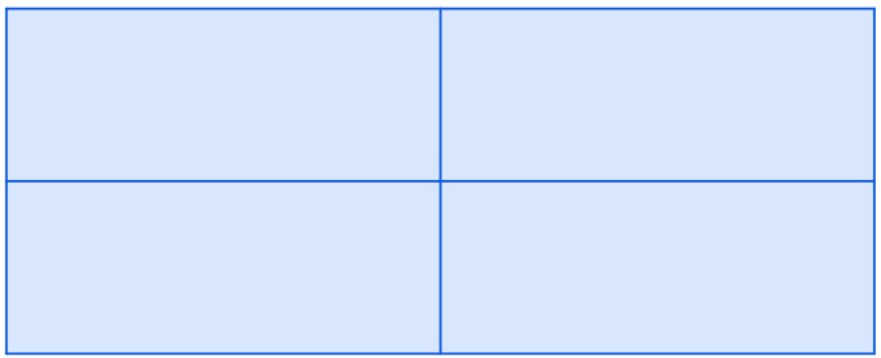

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New		

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	Unstructured (e.g., speech, images)	Structured (e.g., transactions, records)
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Existing		

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

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New	HLP	Are predictive feature available?
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- People are very good on unstructured data tasks
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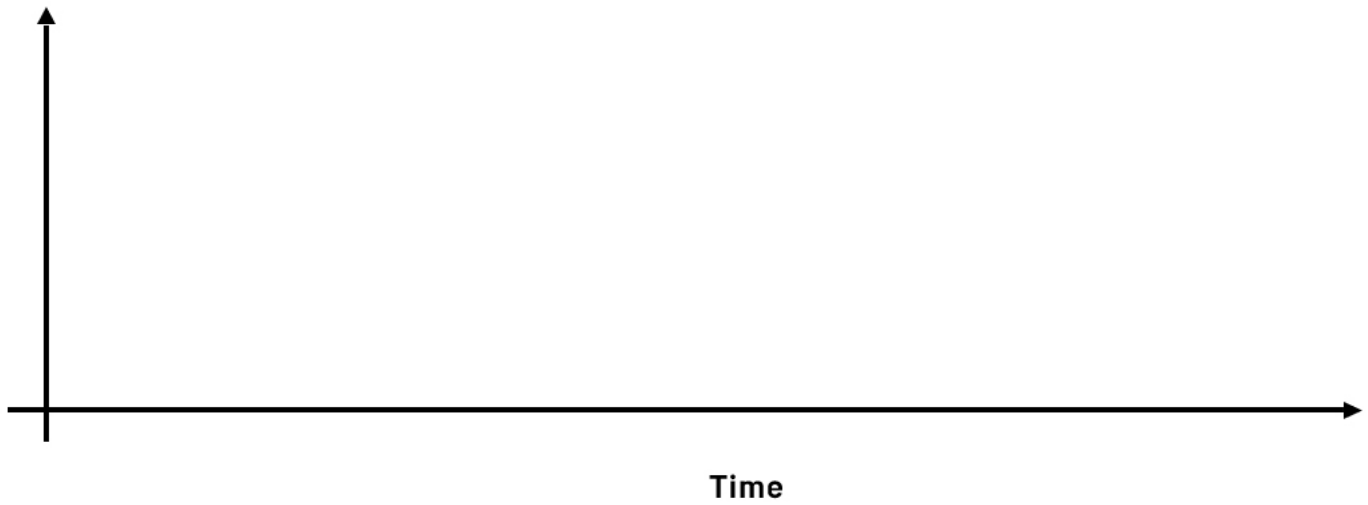
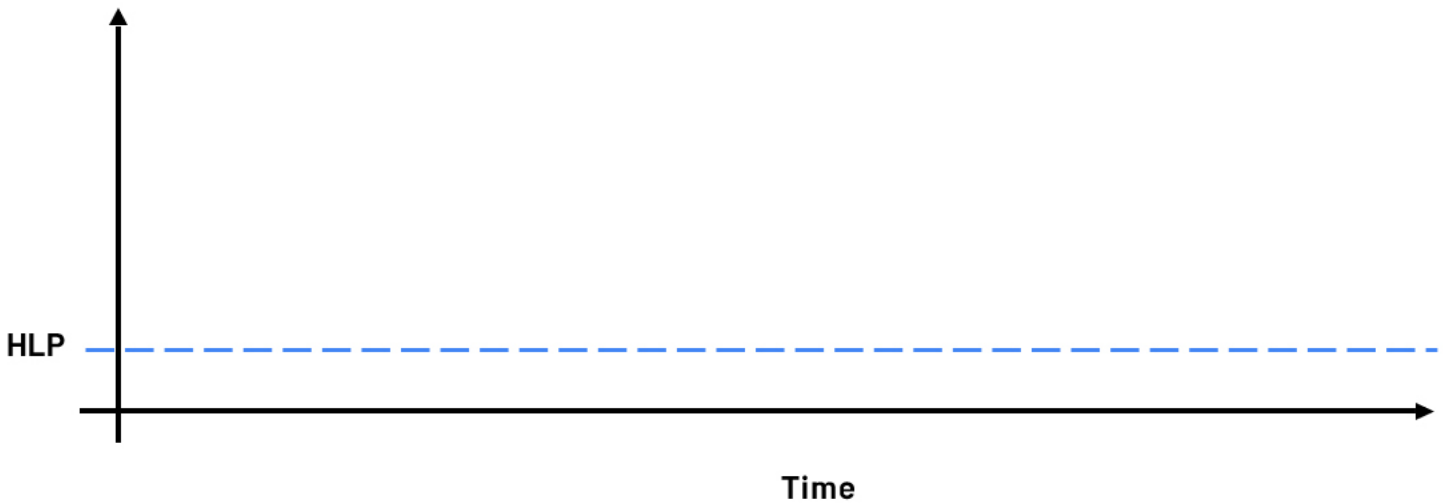
HLP: Can a human, given the same data, perform the task?

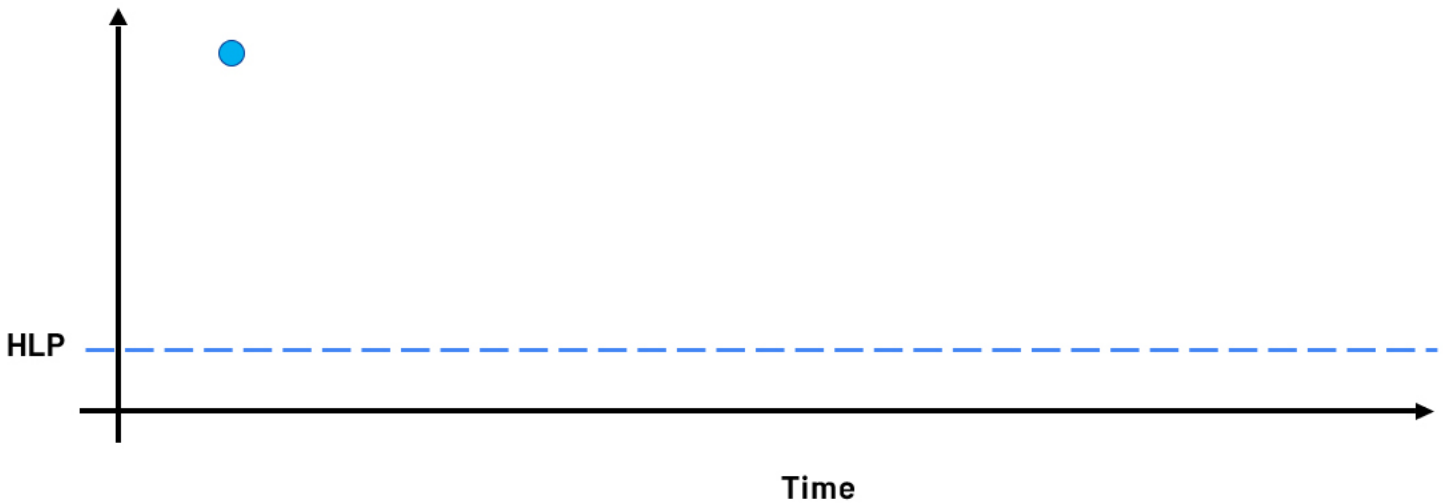
History of project



History of project



History of project



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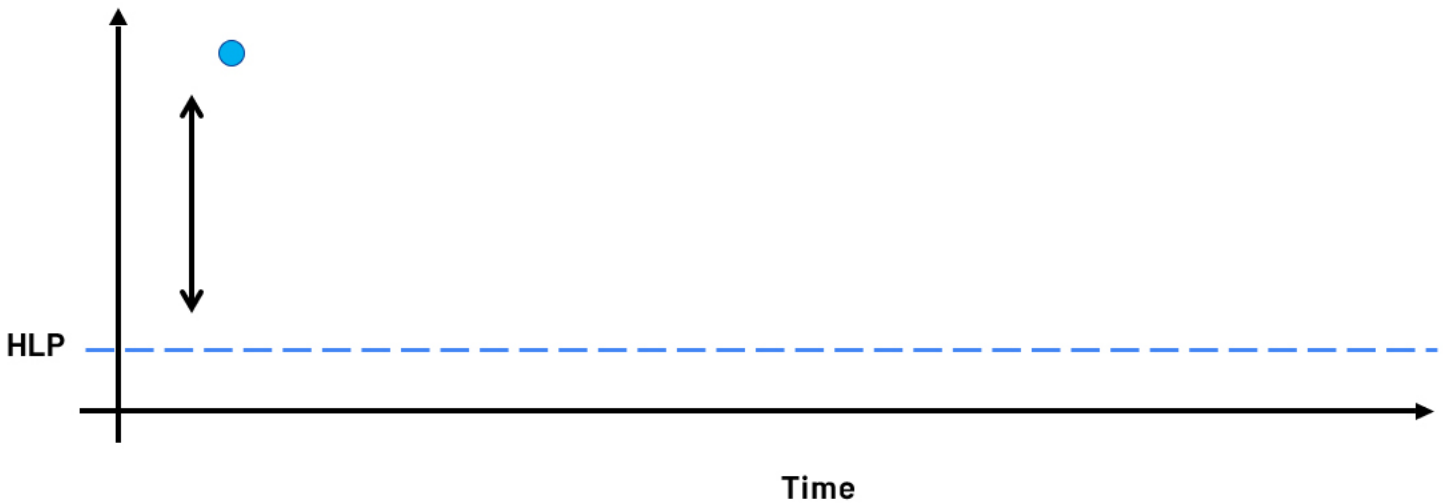

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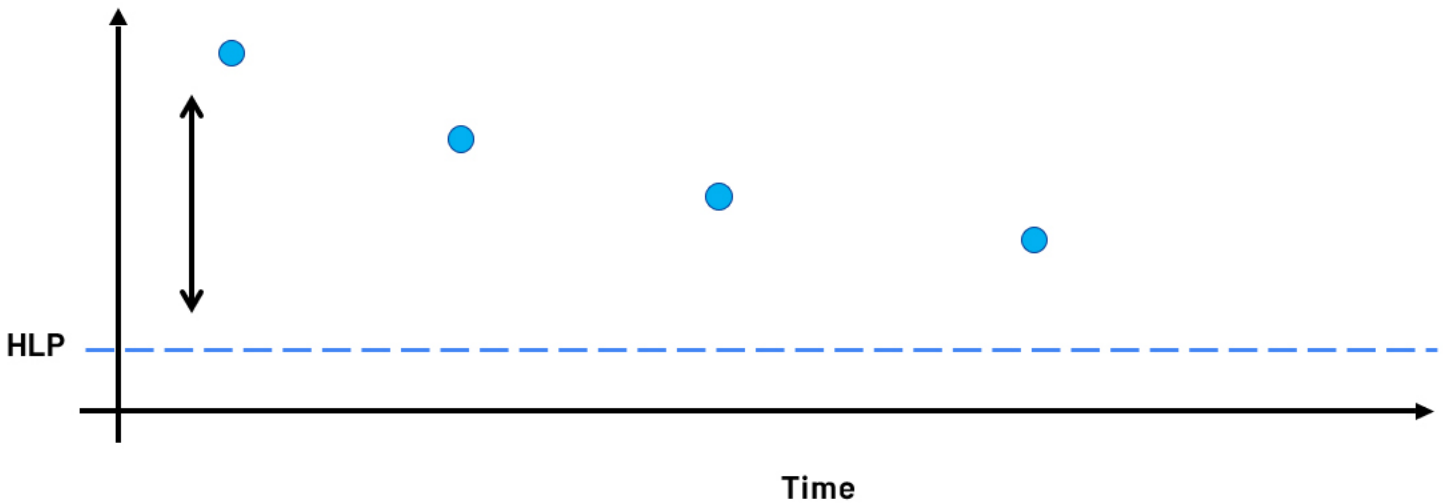
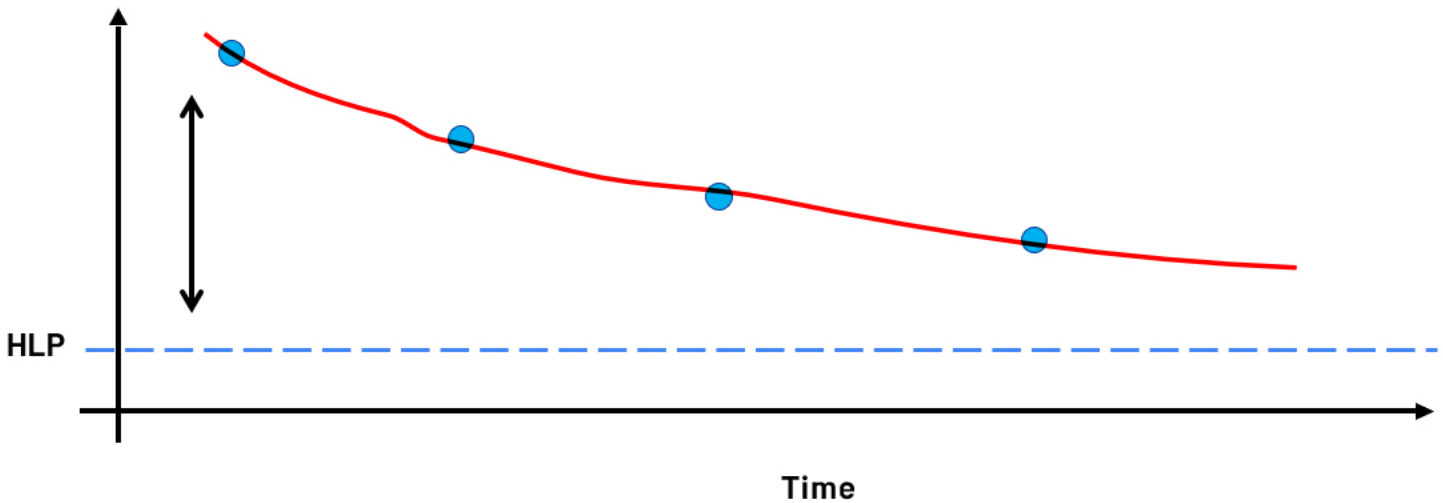


History of project



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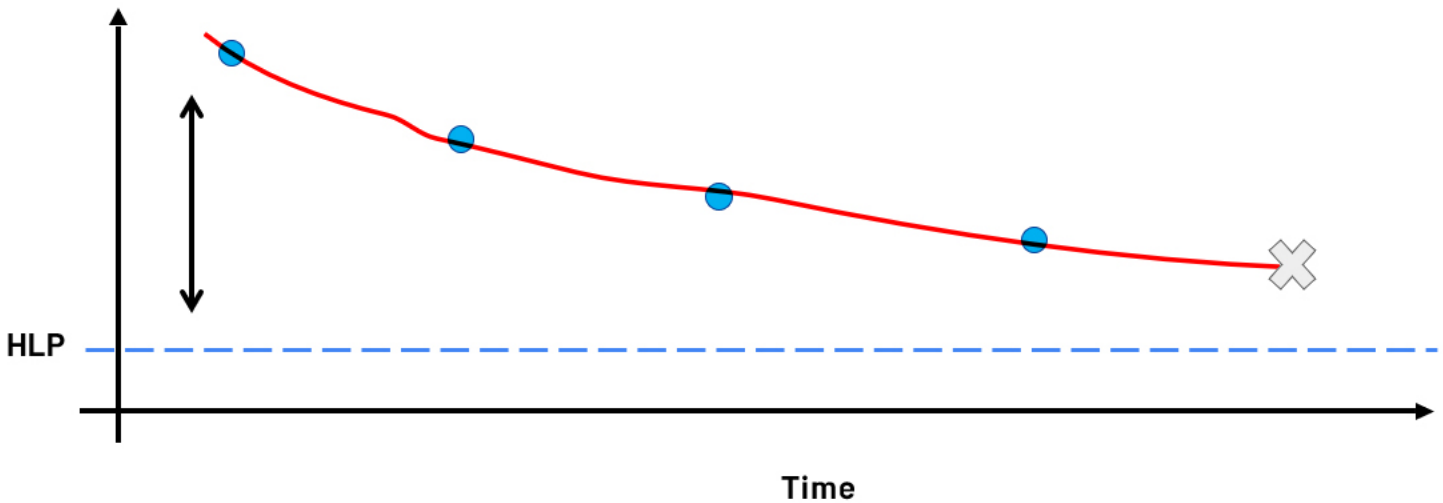


Diligence on value

MLE
metrics

Diligence on value

MLE metrics

Business metrics

Diligence on value

MLE metrics

Business metrics

Word-level accuracy

Diligence on value

MLE metrics

Business metrics

Word-level accuracy

Query-level accuracy

Diligence on value

MLE metrics

Business metrics

Word-level accuracy

Query-level accuracy

Search result quality

Diligence on value

MLE metrics

Business metrics

Word-level accuracy

Query-level accuracy

Search result quality

User engagement

Diligence on value

MLE metrics

Business metrics

Word-level accuracy

Query-level accuracy

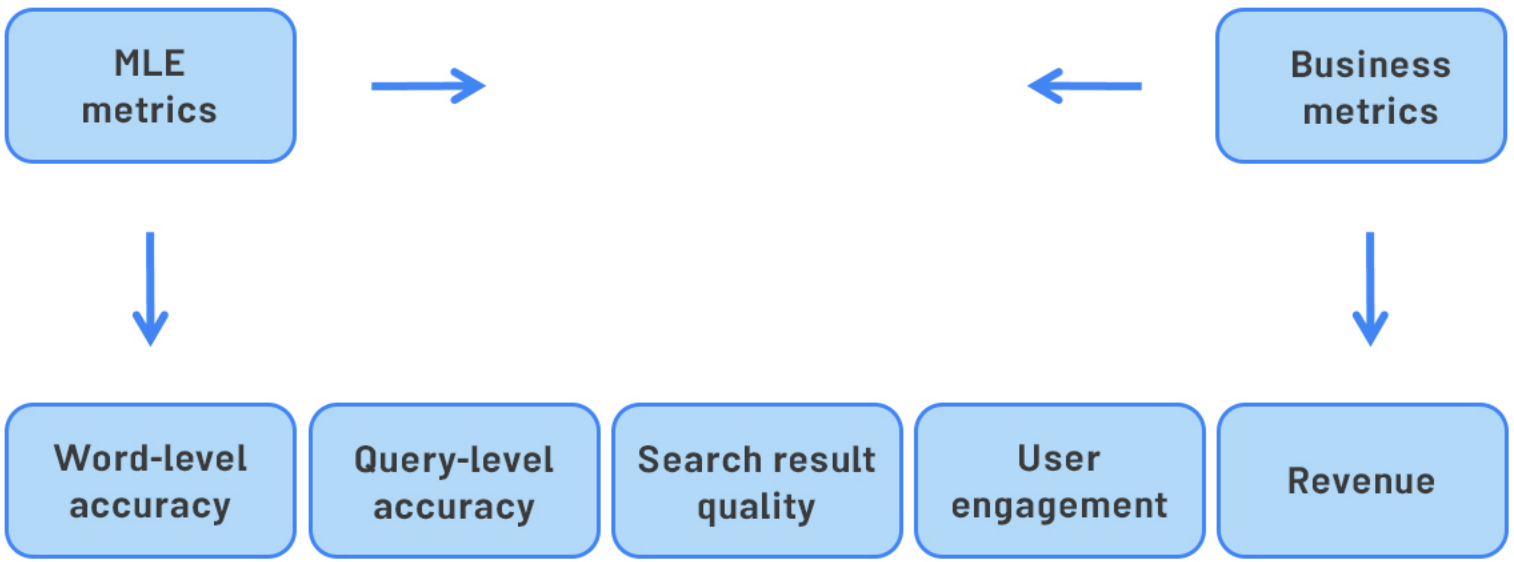
Search result quality

User engagement

Revenue

Diligence on value

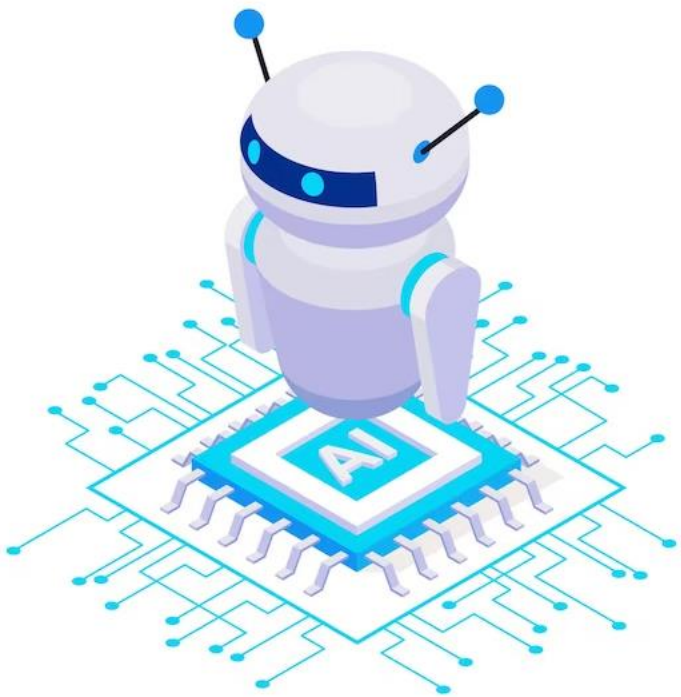
Diligence on value



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

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?



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.