Machine Learning Basics

Neuroinformatics Tutorial 1

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Content

- Motivation
- When does a Machine learn?
- Machine Learning tasks
- Broad types of Machine Learning Algorithms
- How do input/output look like?
- Data partitioning

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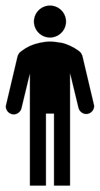

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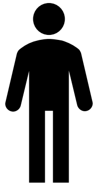

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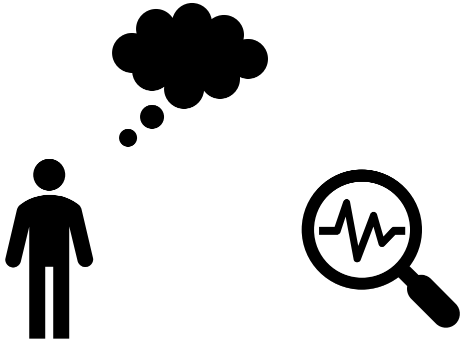

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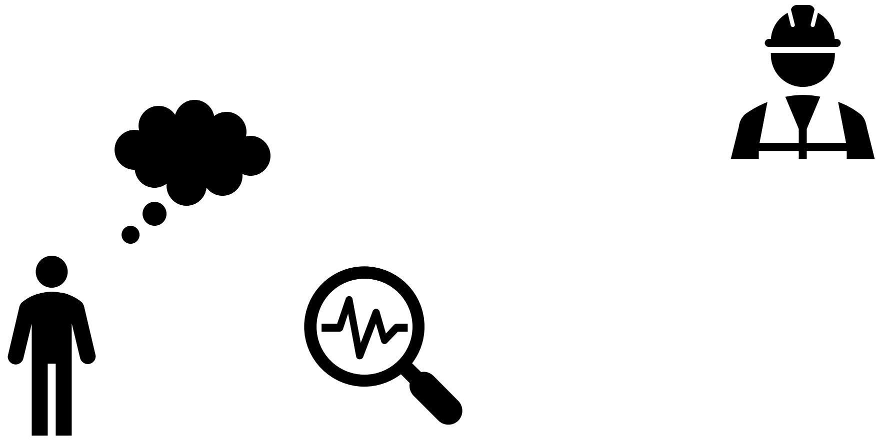

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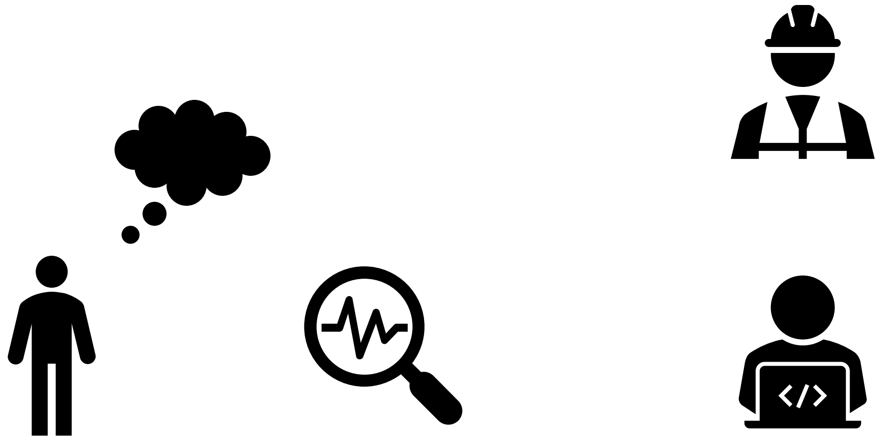

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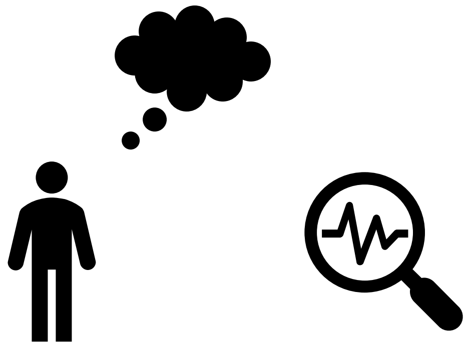

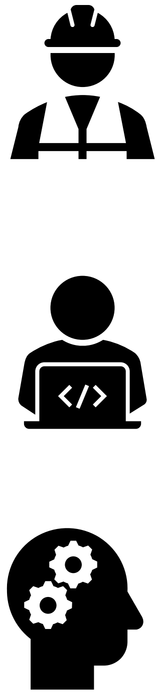

Motivation

Observation

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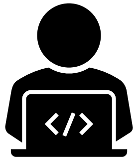
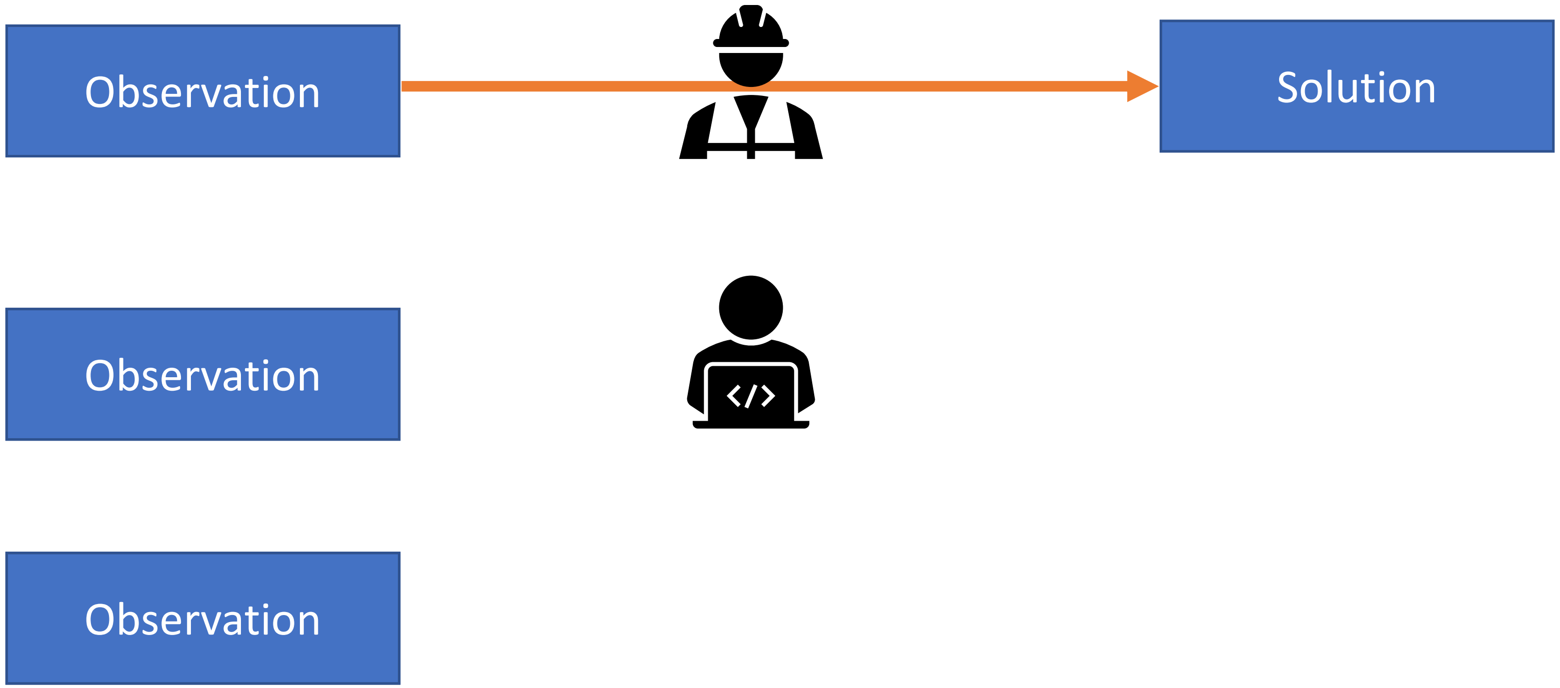


Observation

Motivation



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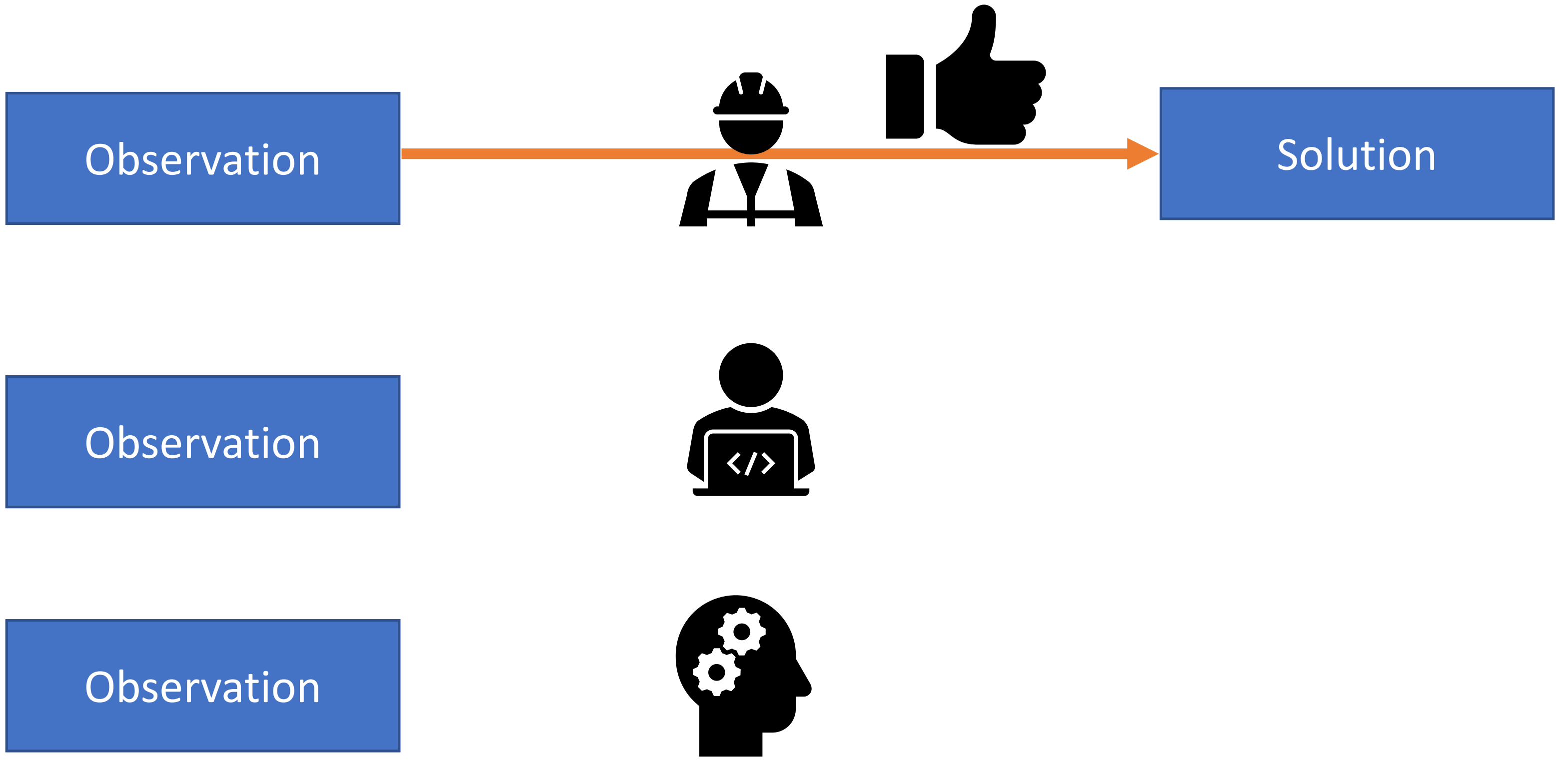

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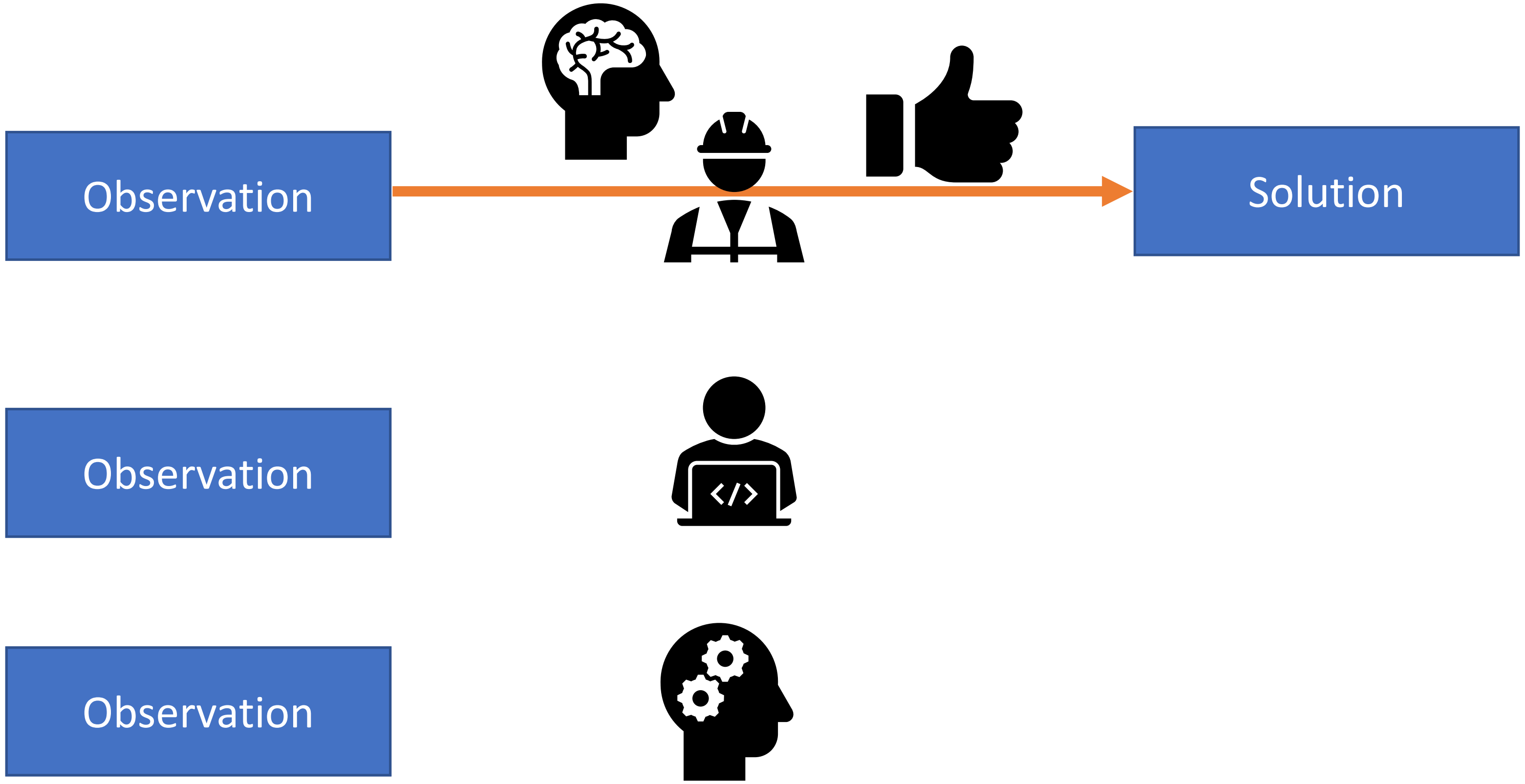

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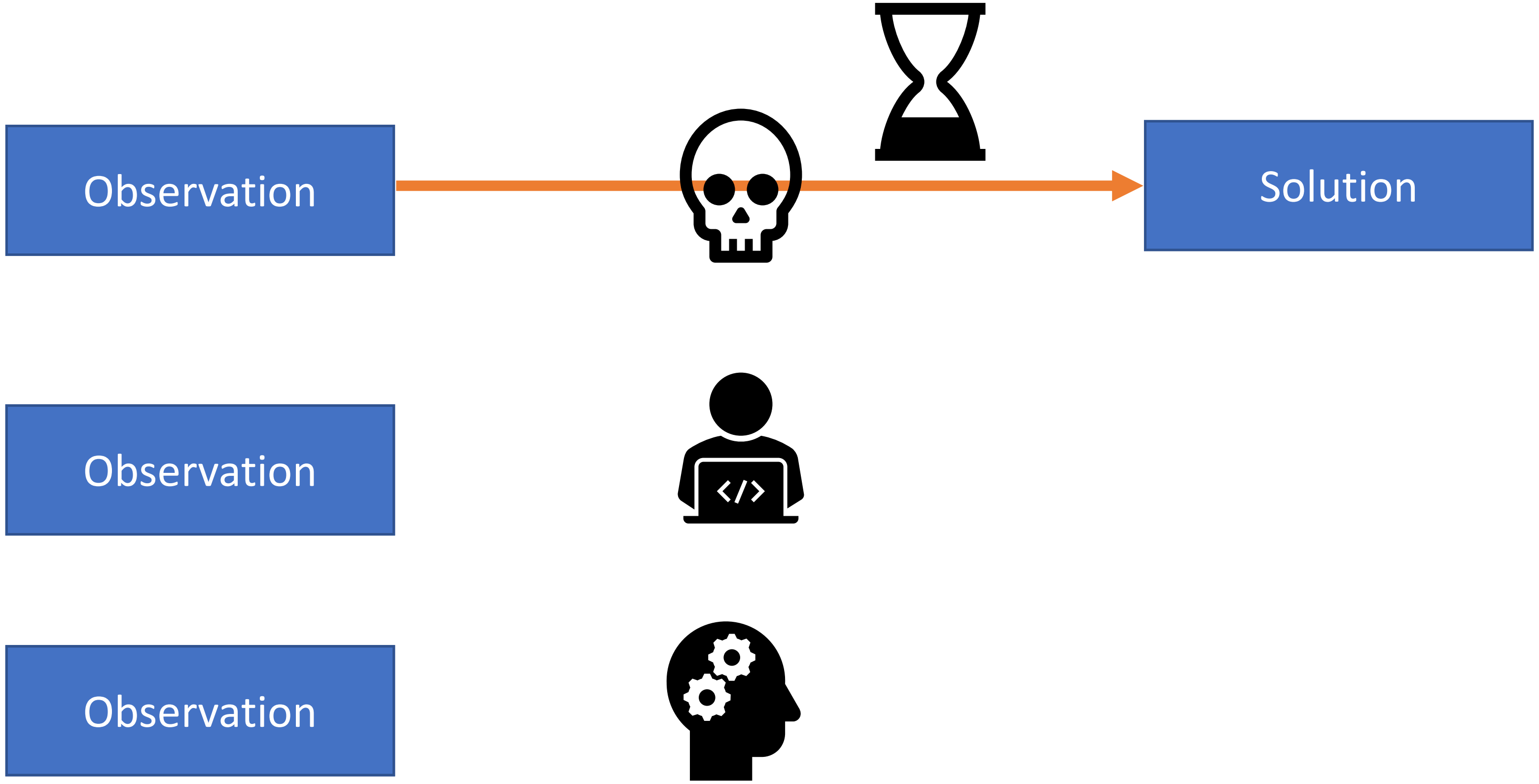

Can be very time consuming!

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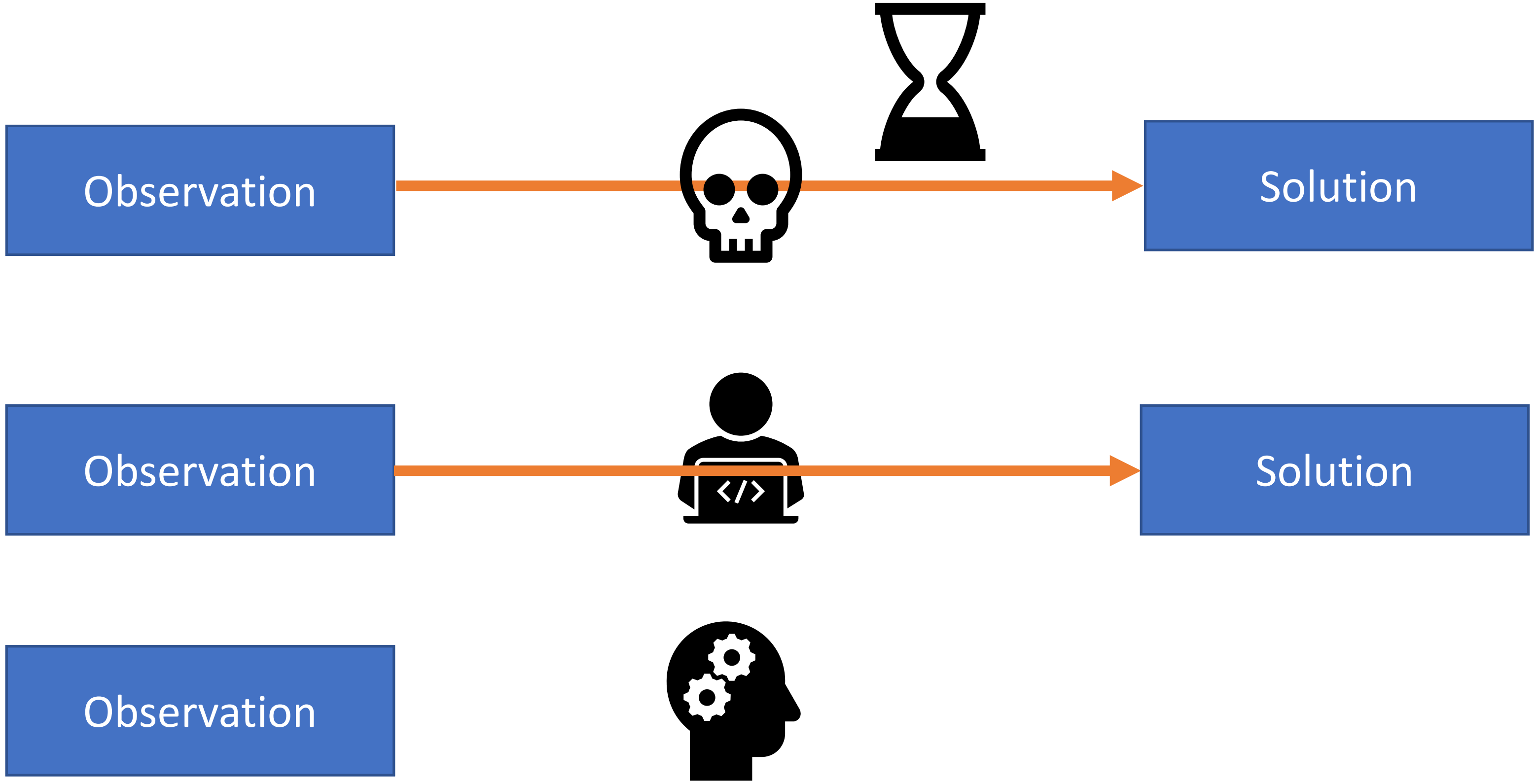

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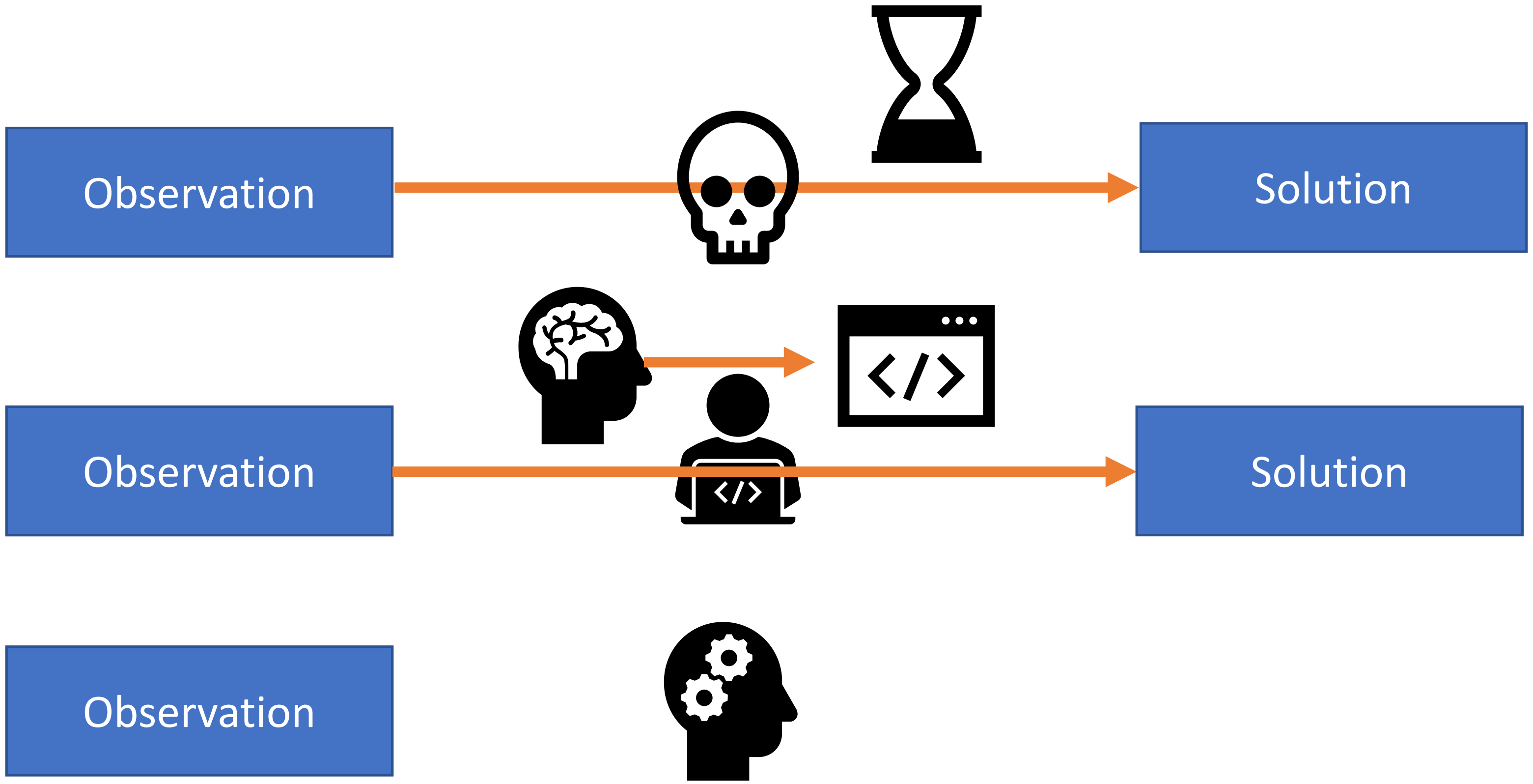

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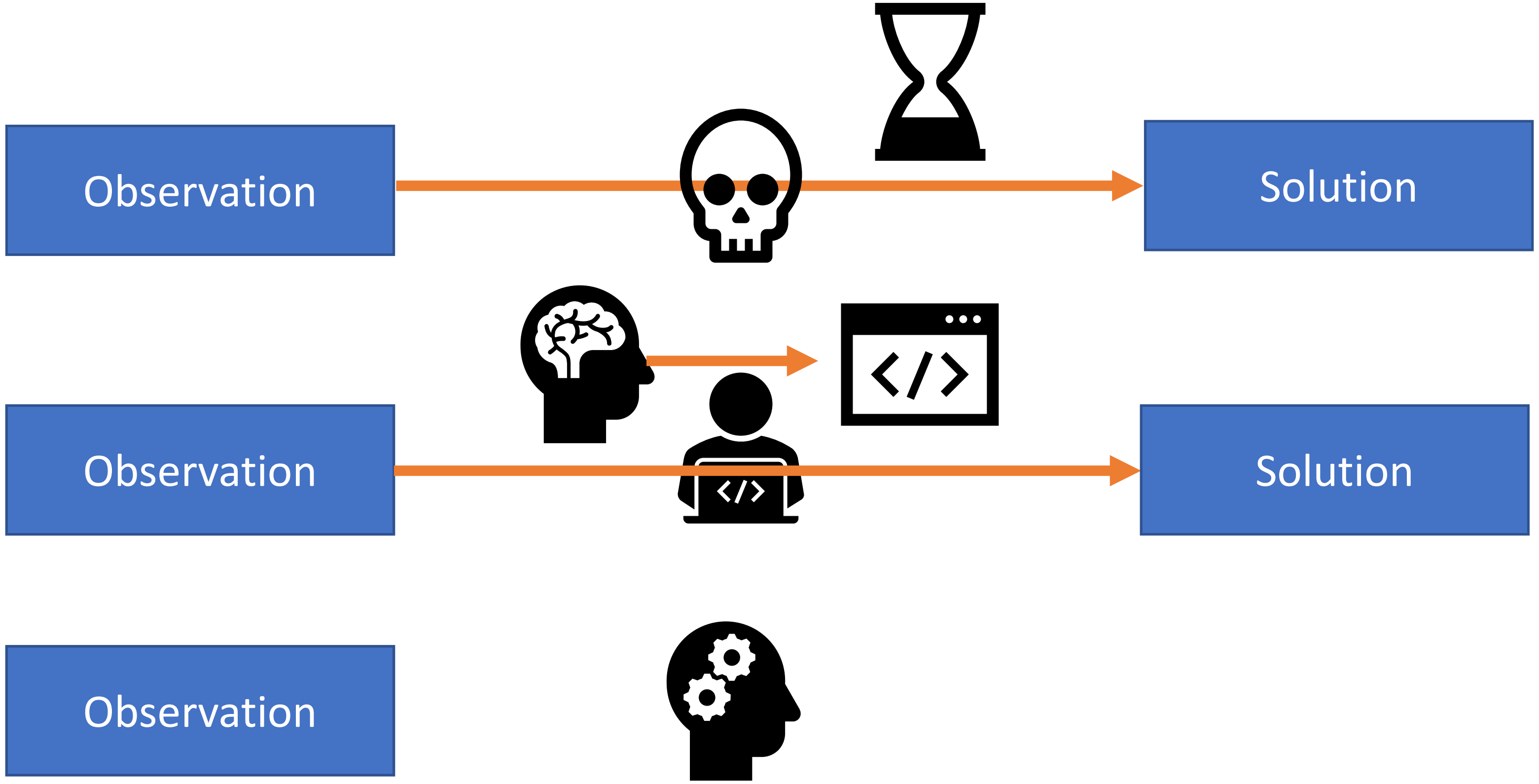

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May lack generalizability

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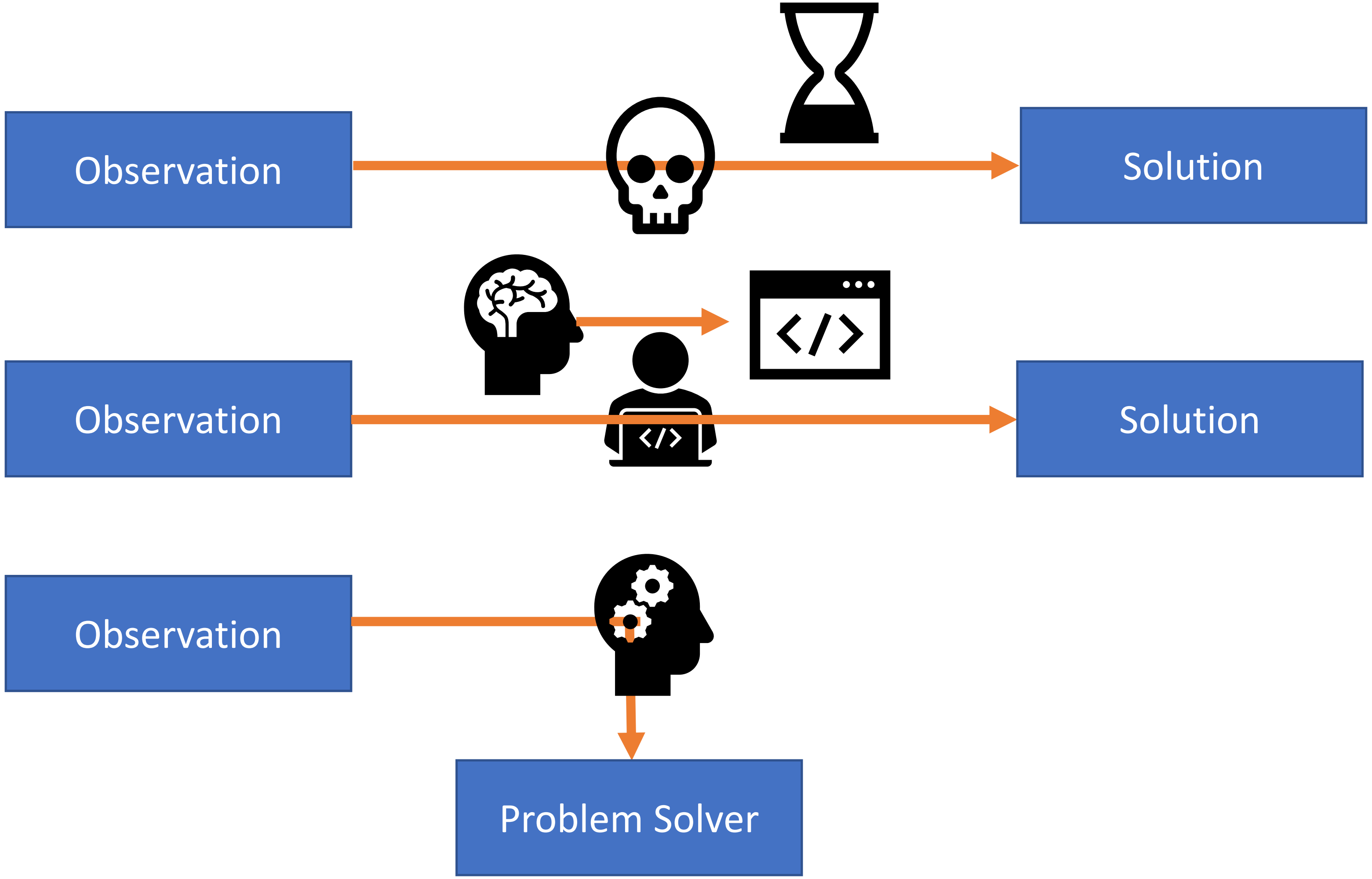

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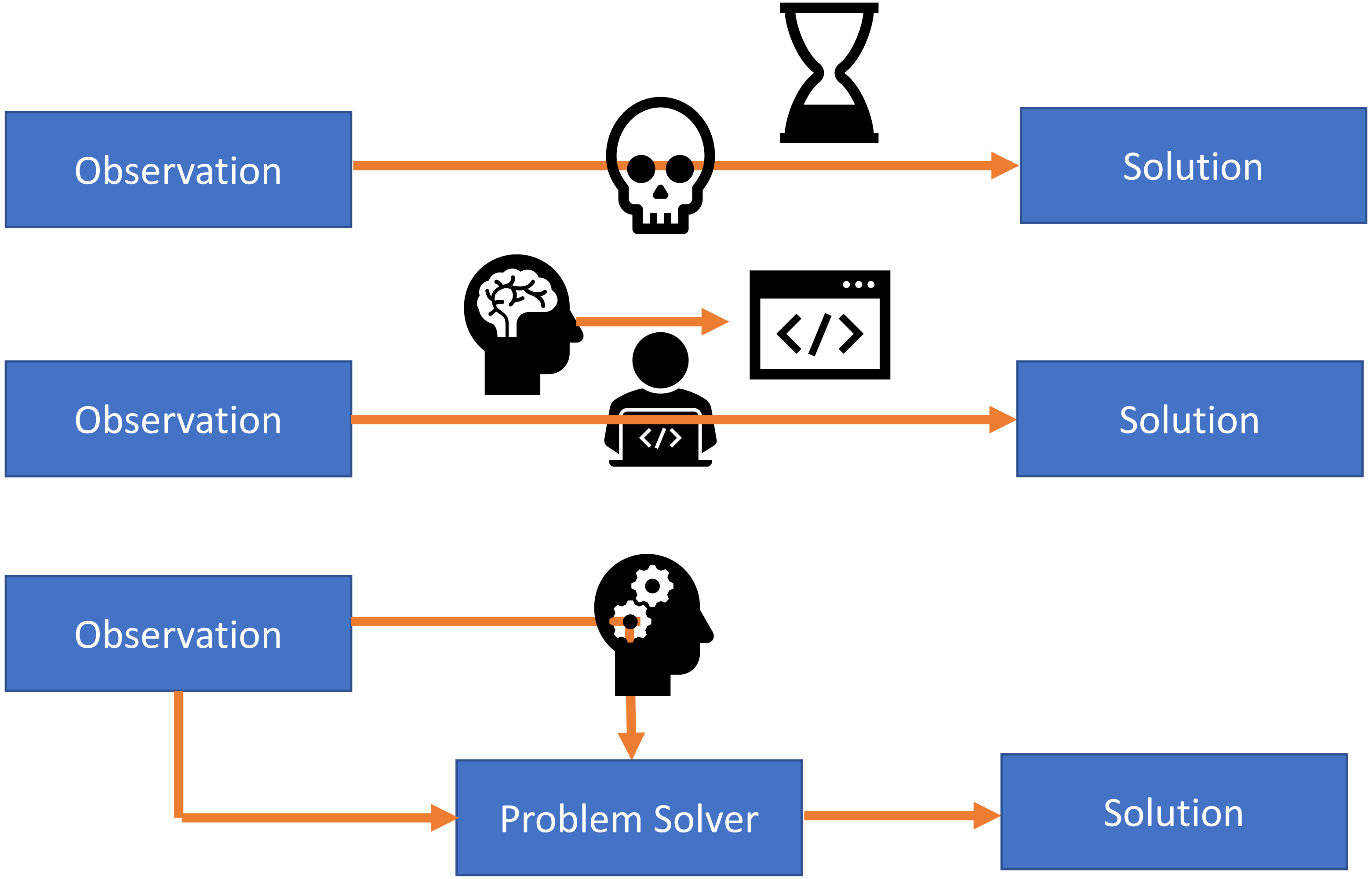

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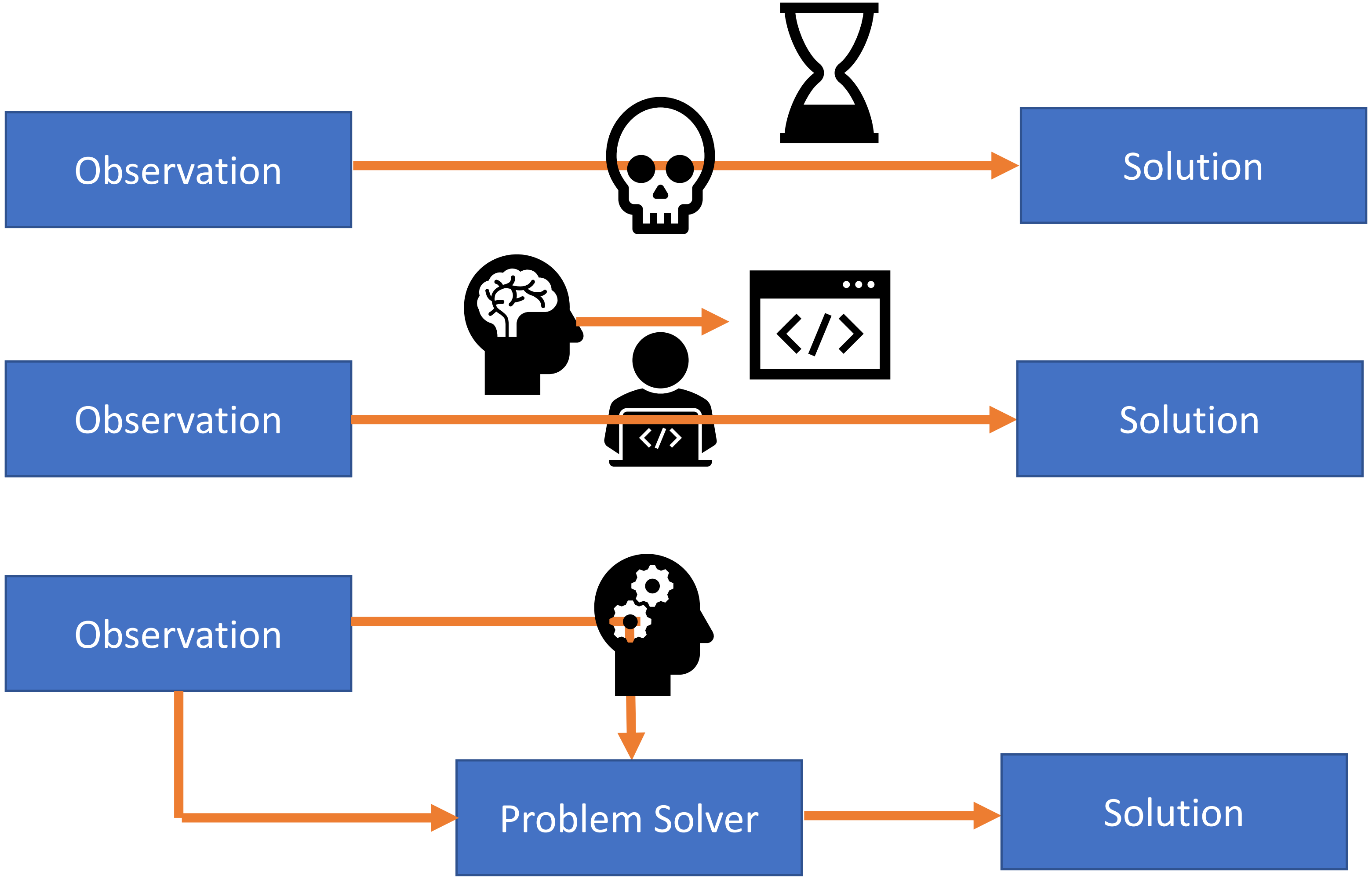
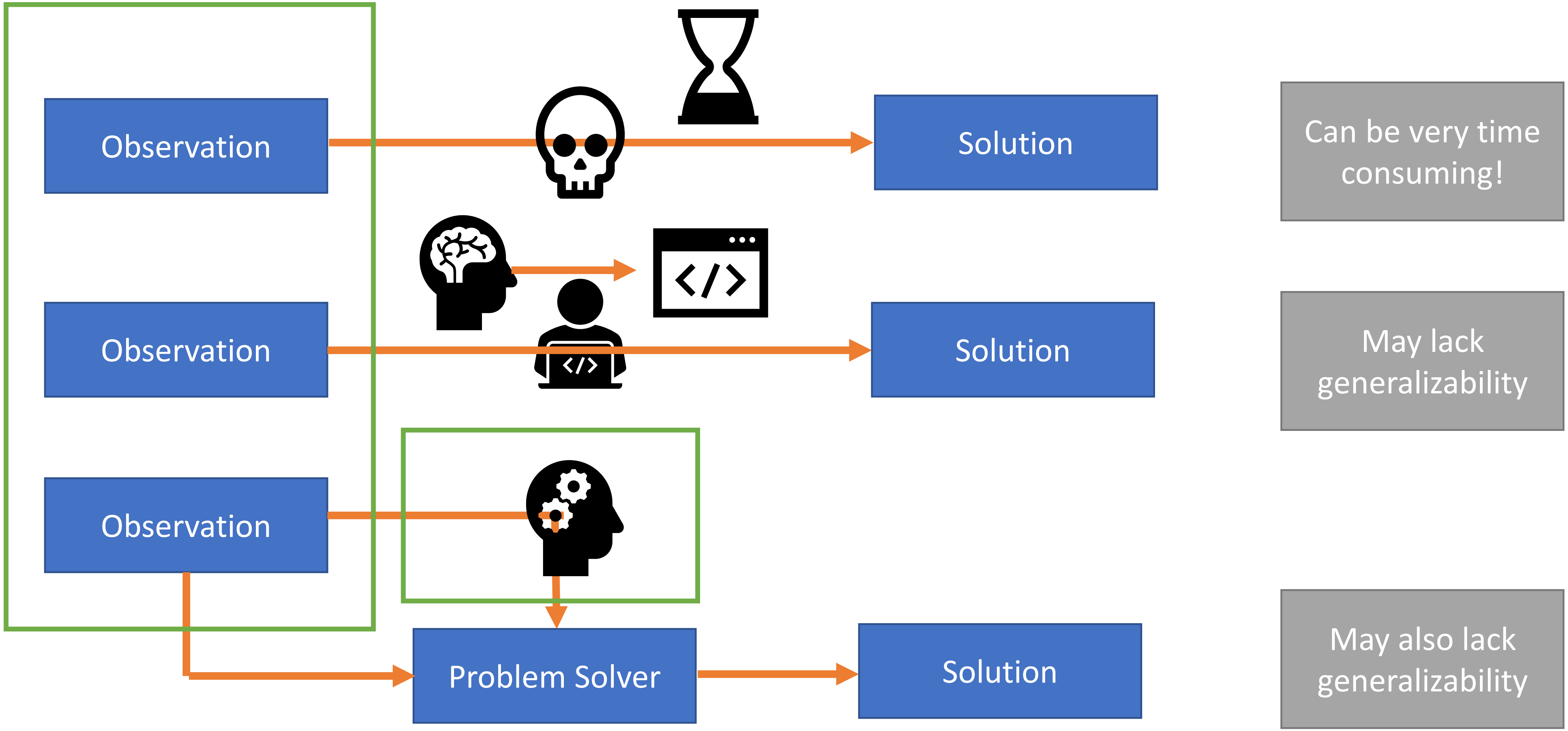


Can be very time consuming!

May lack generalizability

May also lack generalizability

Motivation


Observation
Observation
Observation
Solution
Solution
Solution
Problem Solver
Can be very time consuming!
May lack generalizability
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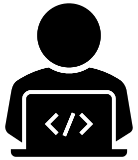
Difference Coding and ML?



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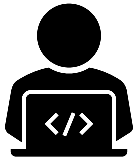

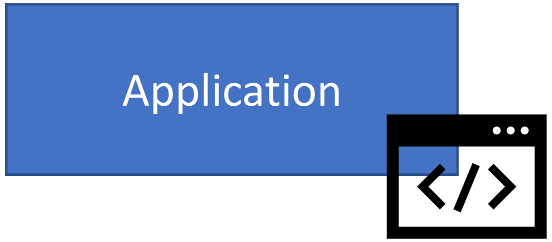

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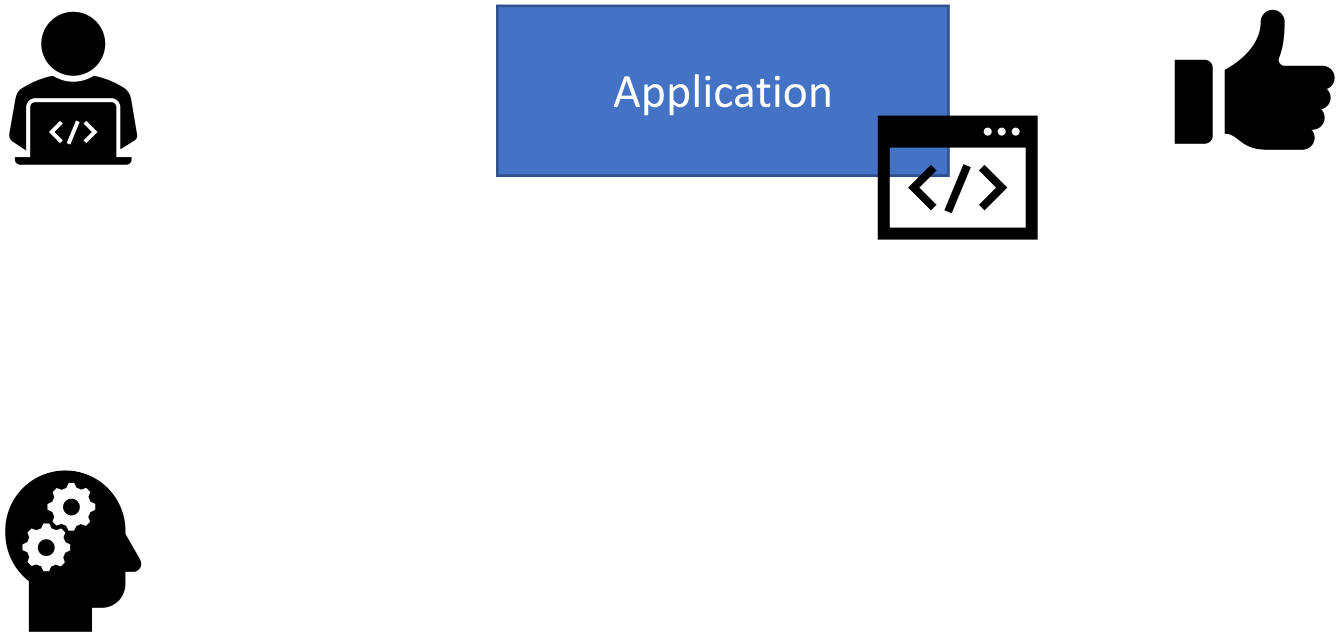

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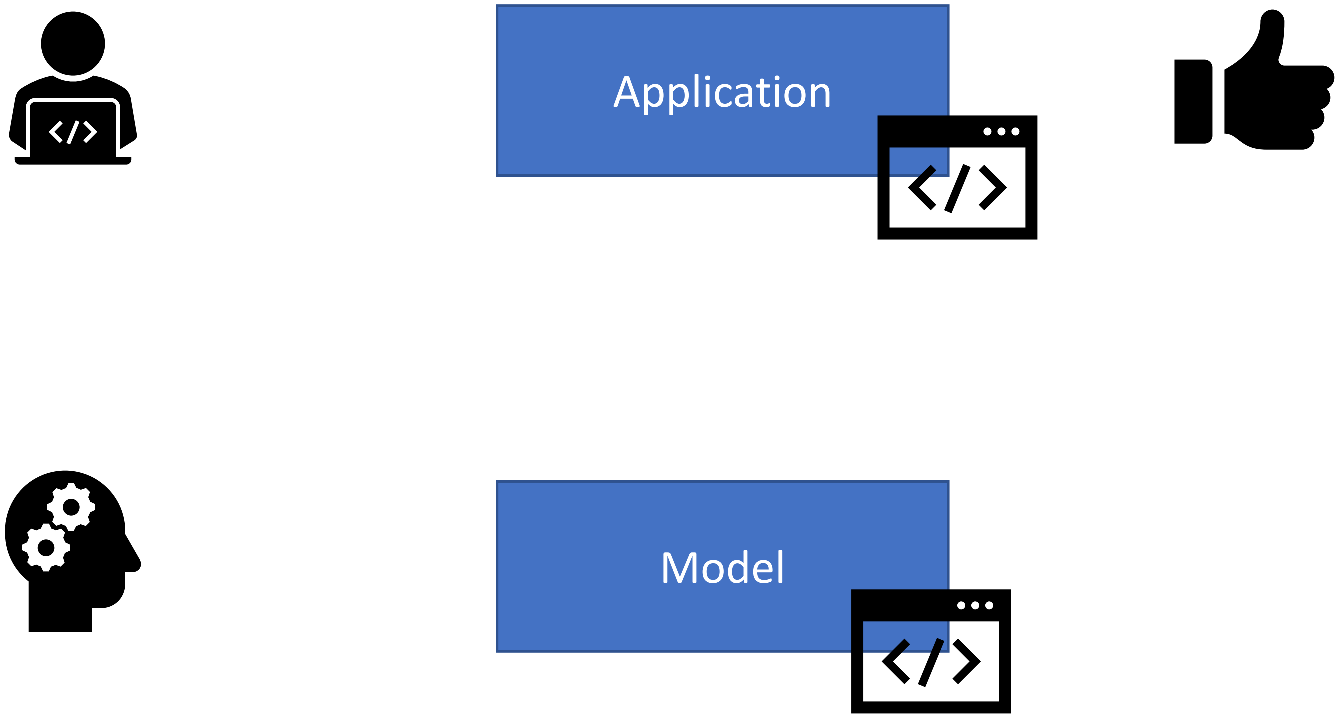

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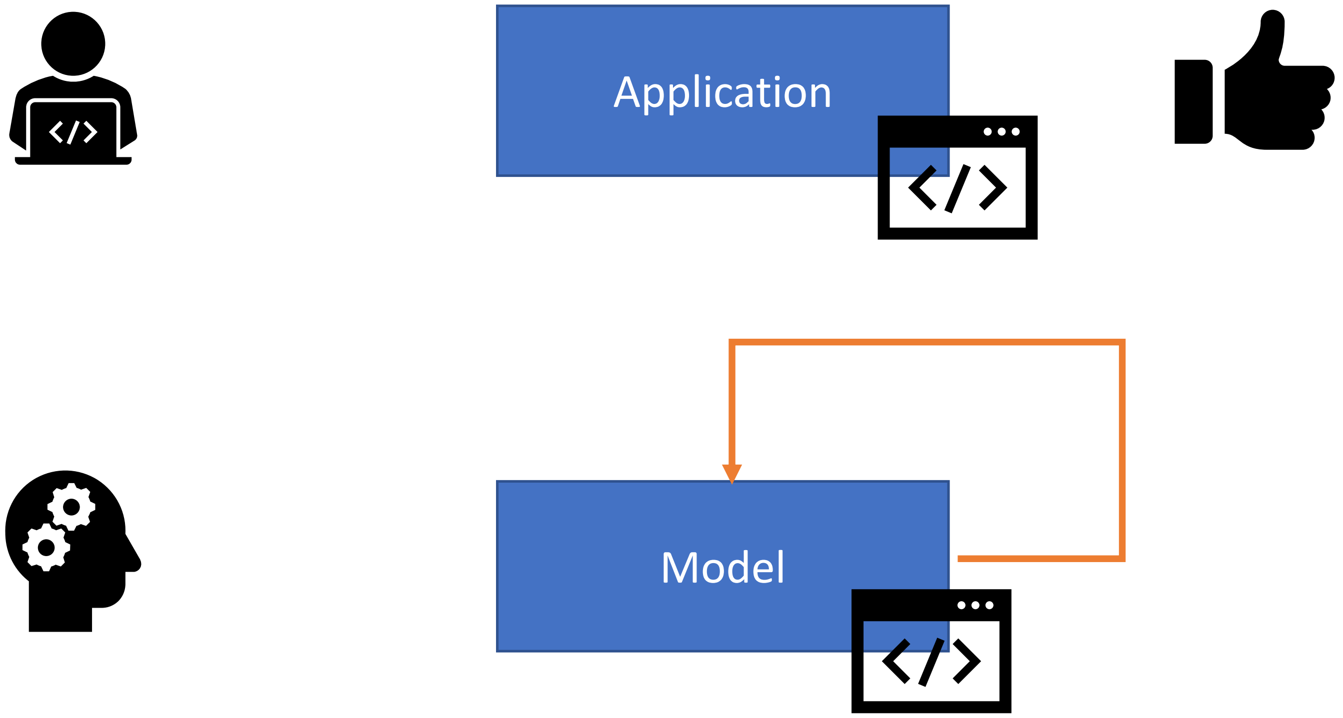

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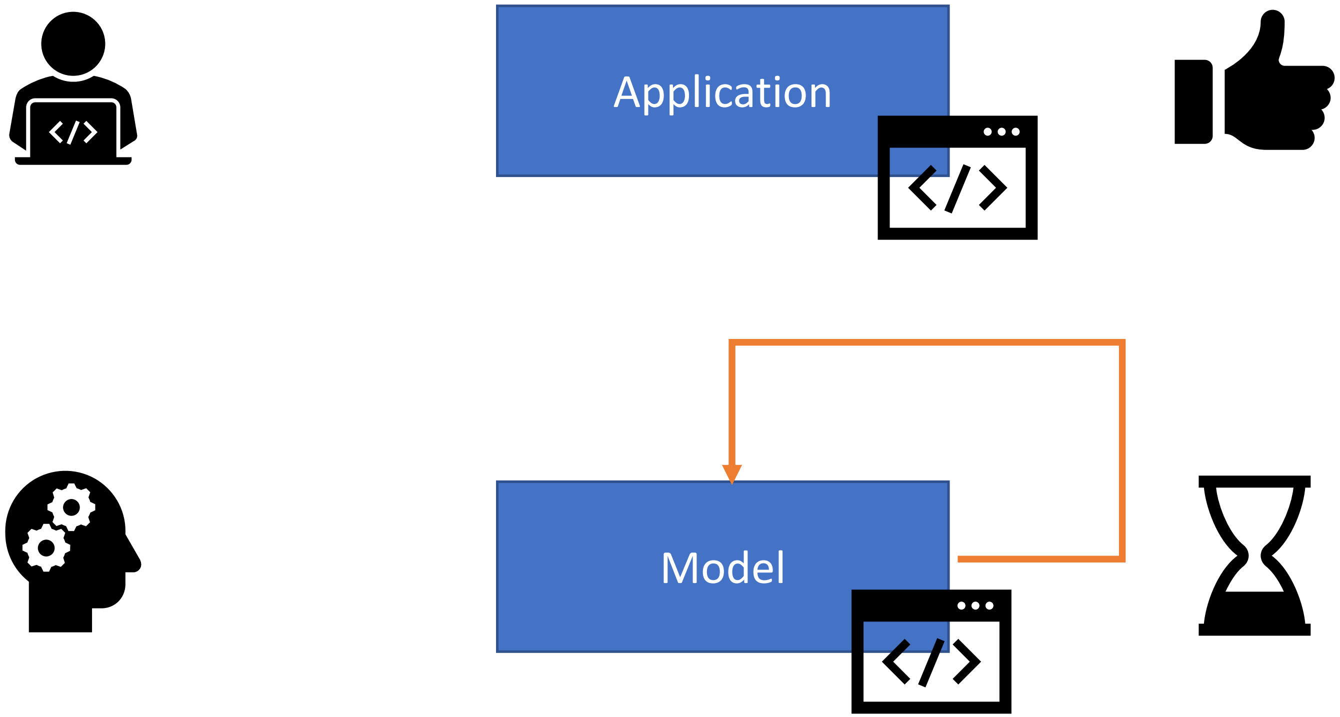

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When does a Machine learn?

Mitchell (1997):
„A computer is said to learn from experience E*,*
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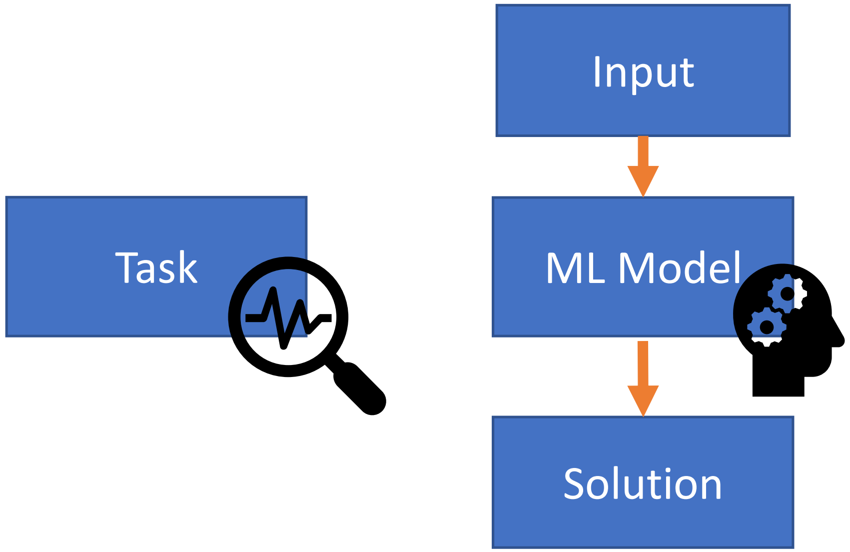

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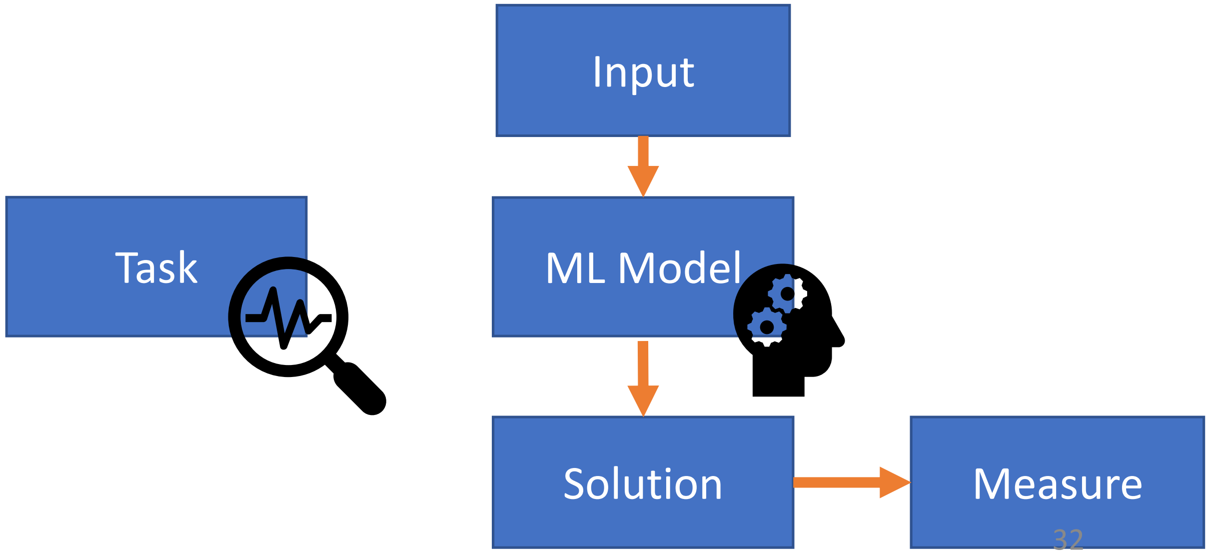

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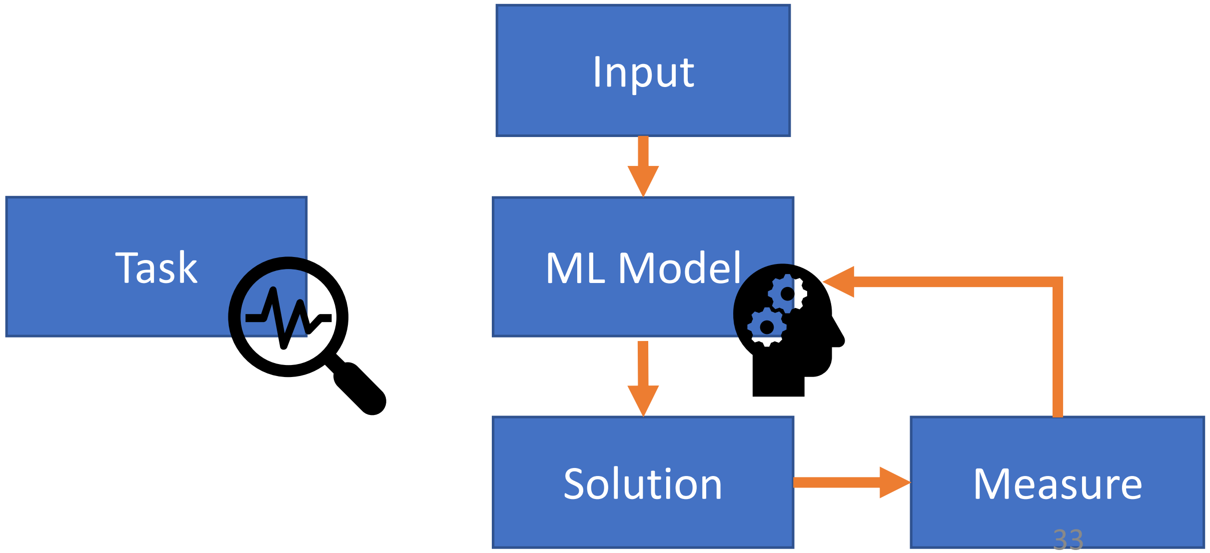

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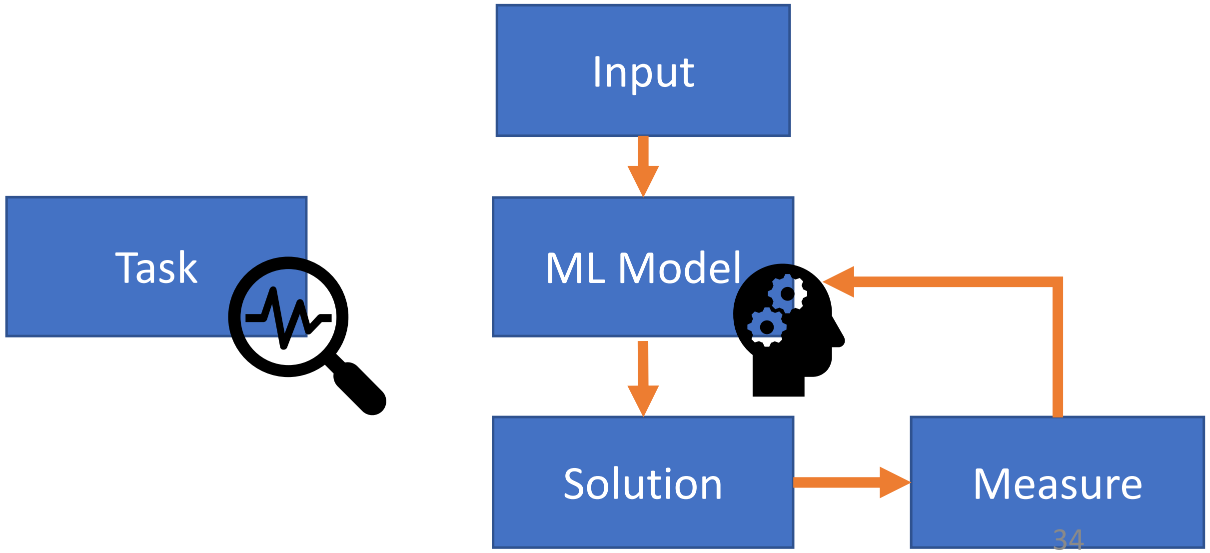

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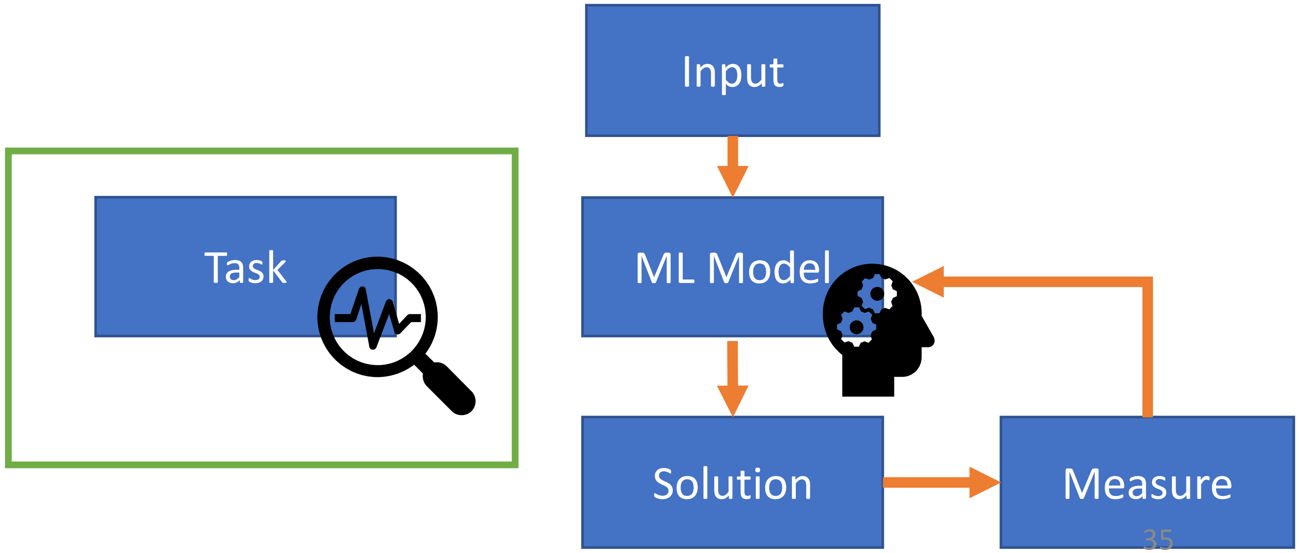

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Tasks

- Typical tasks:
  - Classification

Classification

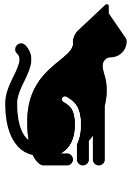
ML Model

Cat

Dog

Bird

Classification



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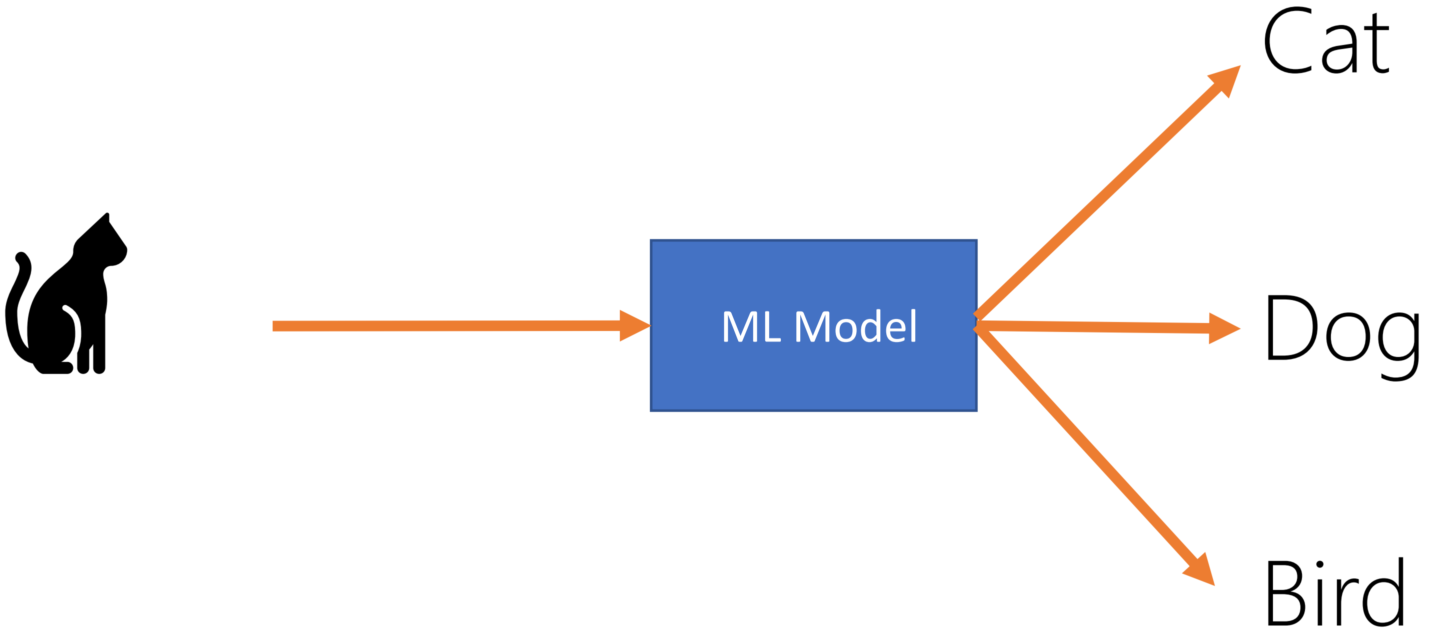

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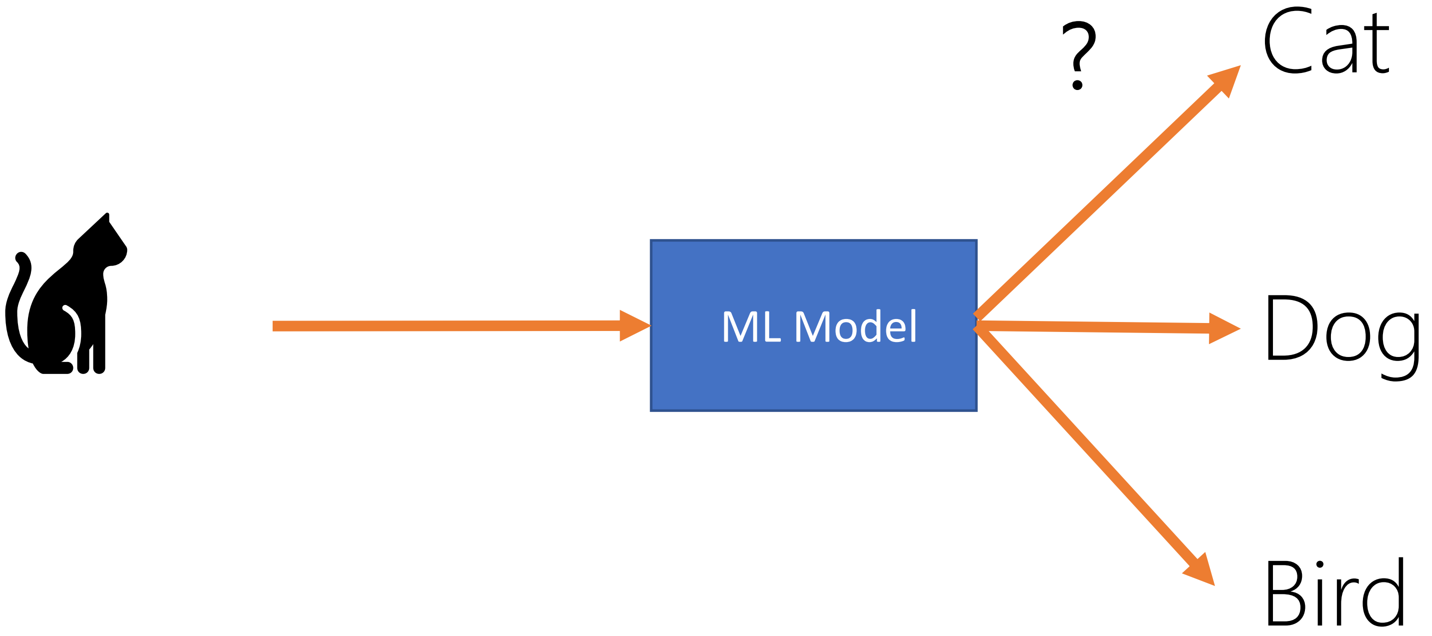

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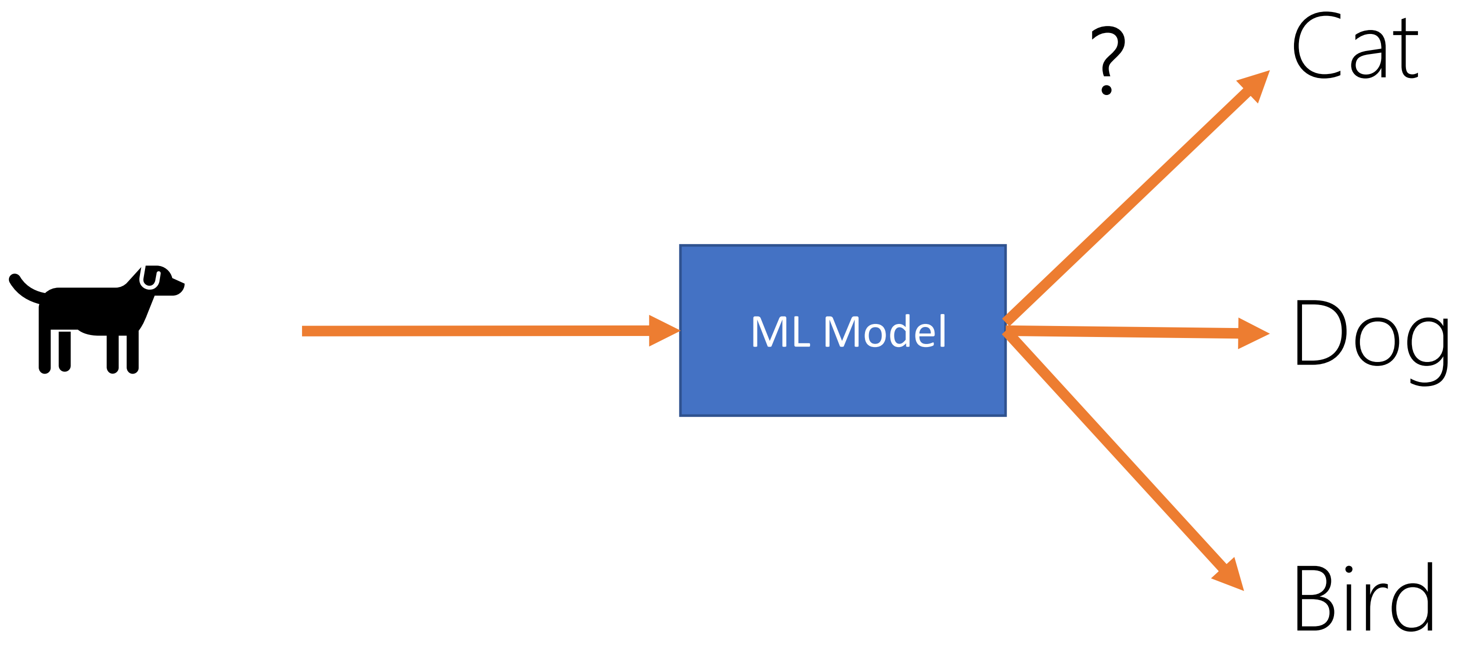

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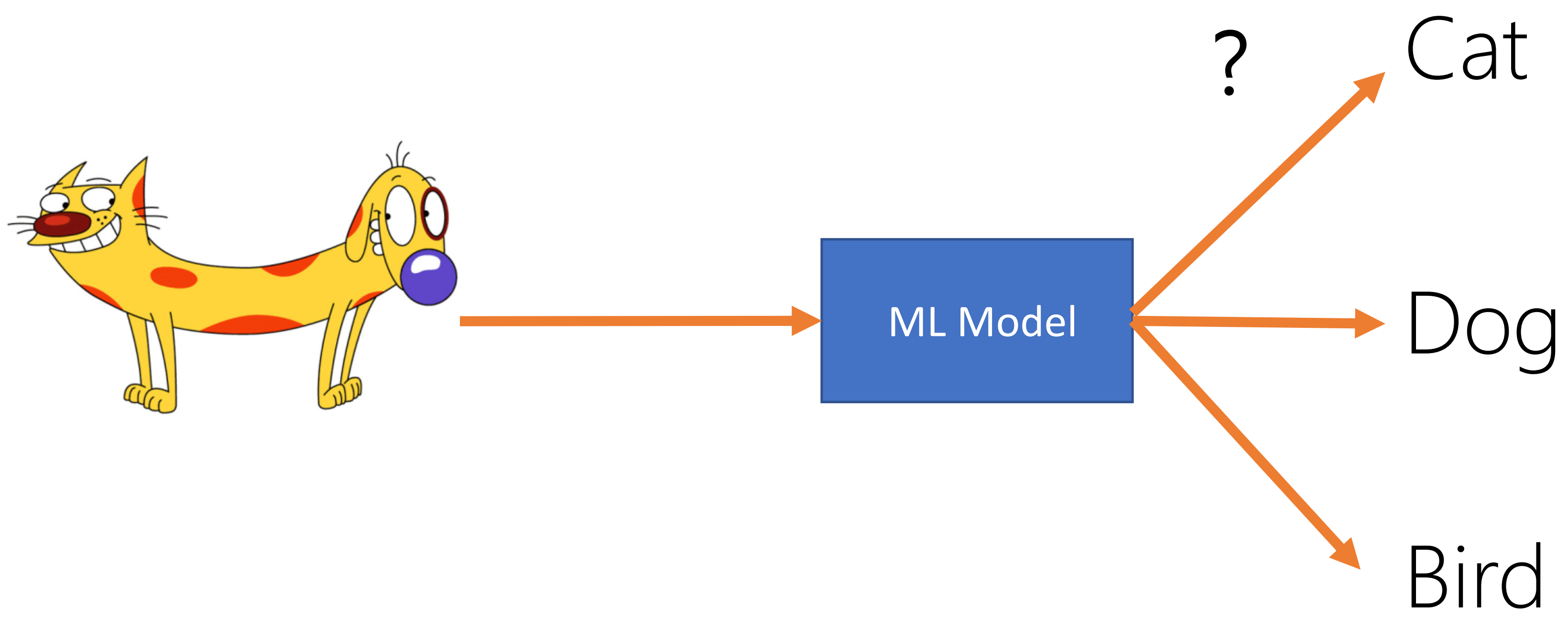
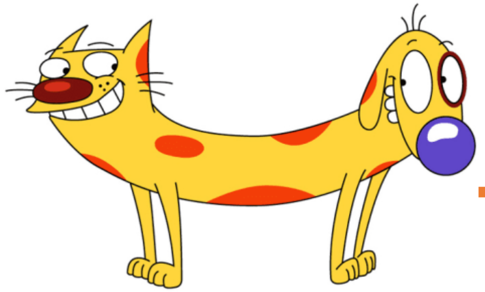


https://www.buzzfeed.com/lyapalater/how-does-catdog-poop

Classification



ML Model

?

Cat

Dog

Bird

Categorical Output!

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Tasks

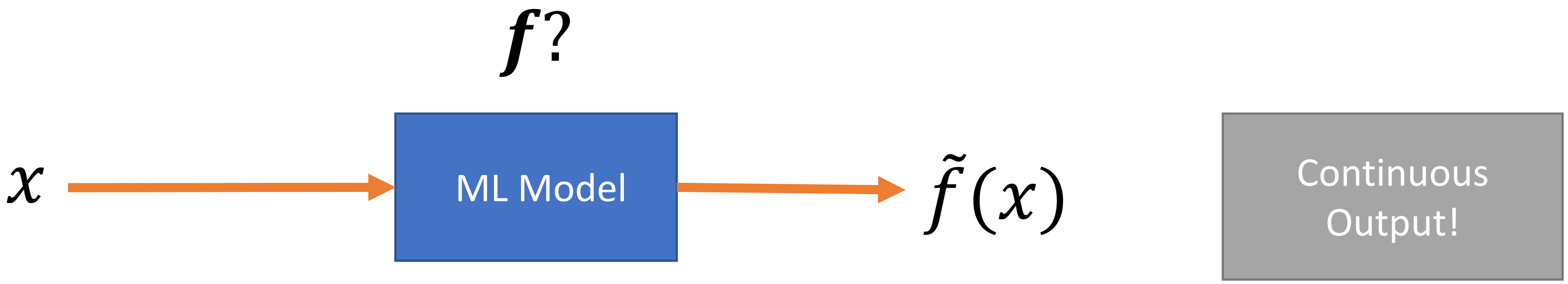
- Typical tasks:
  - Classification
  - Regression

Regression

ML Model

Regression

Regression



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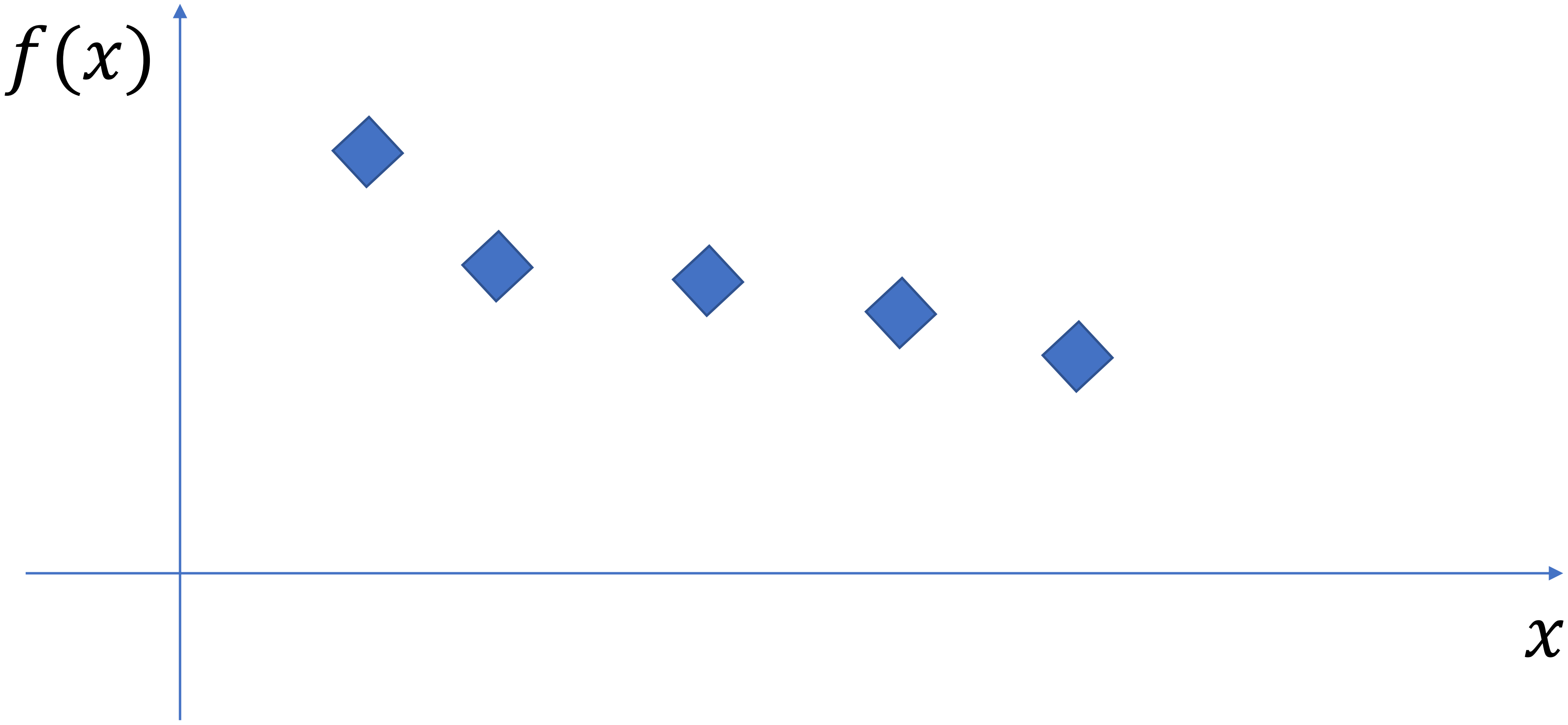

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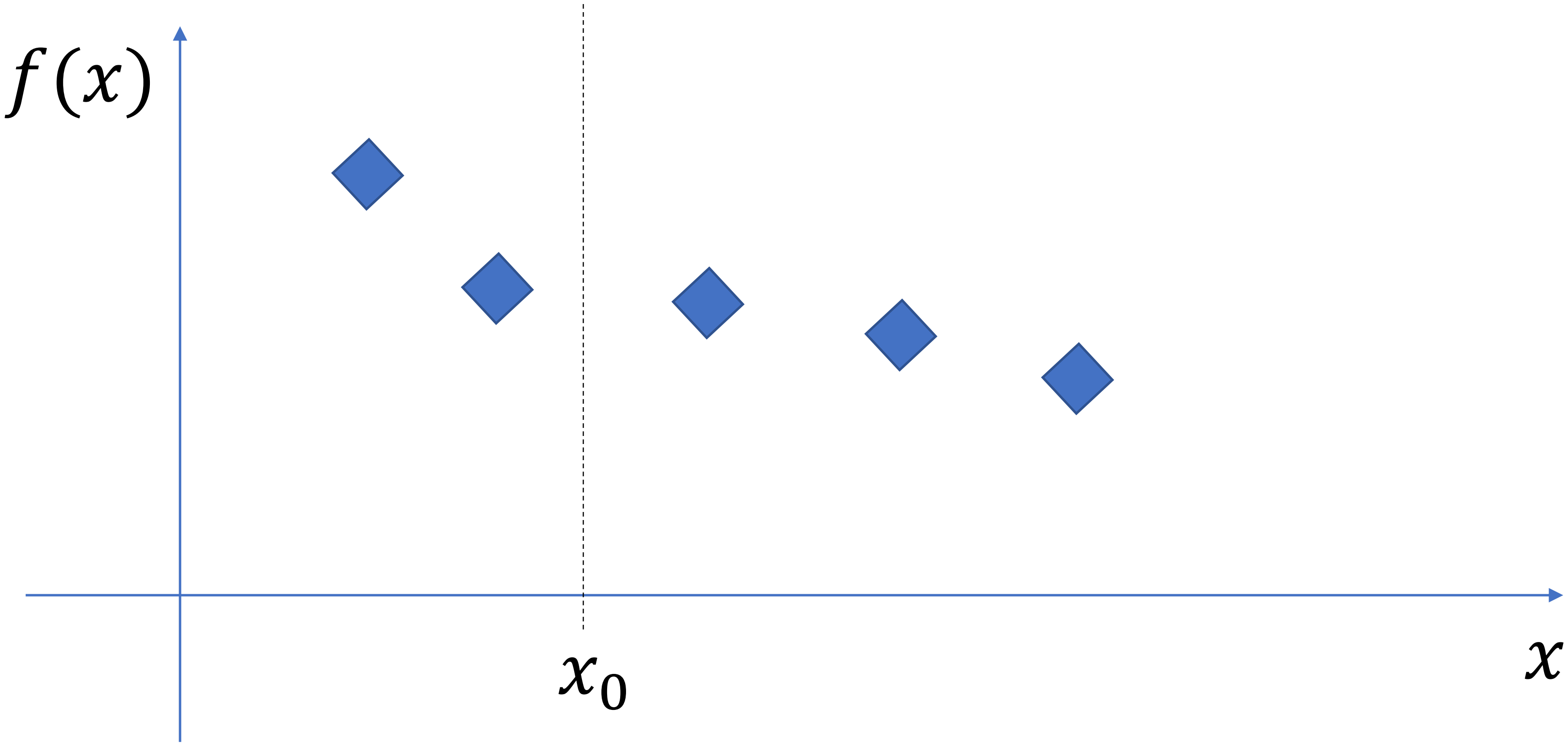

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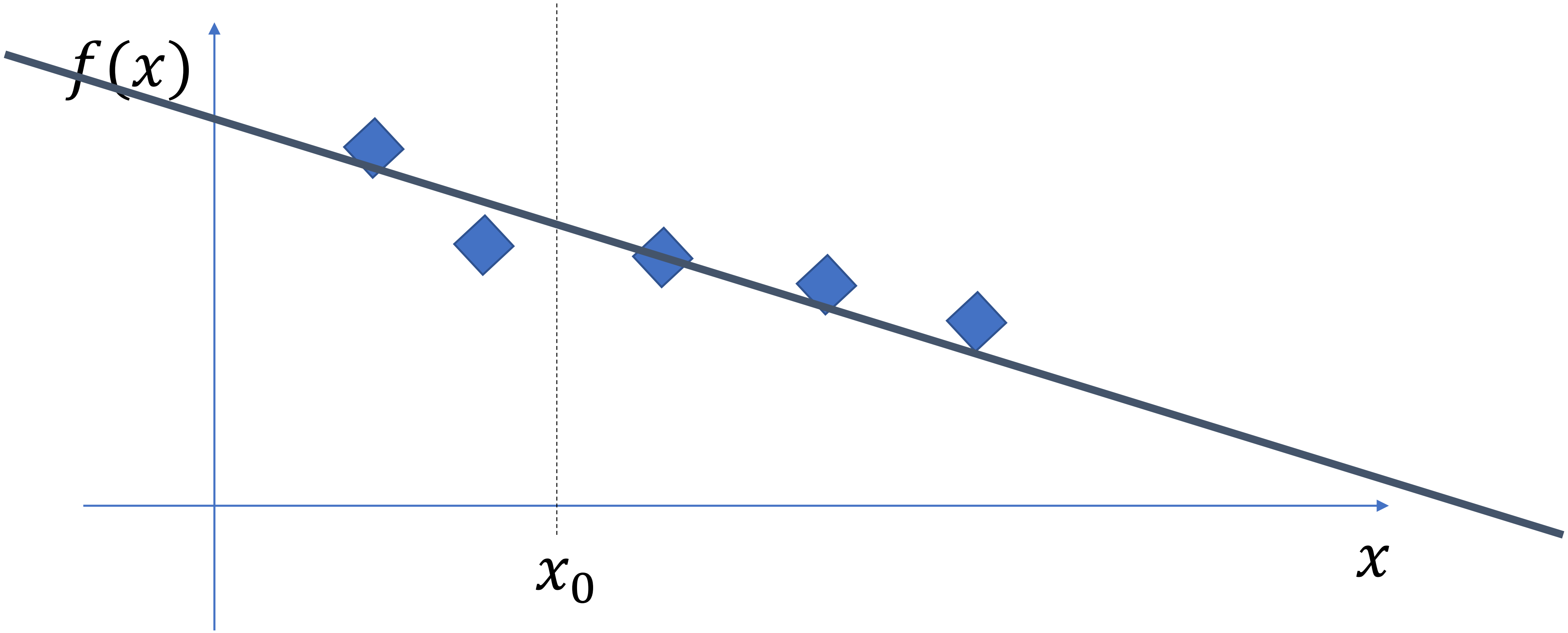

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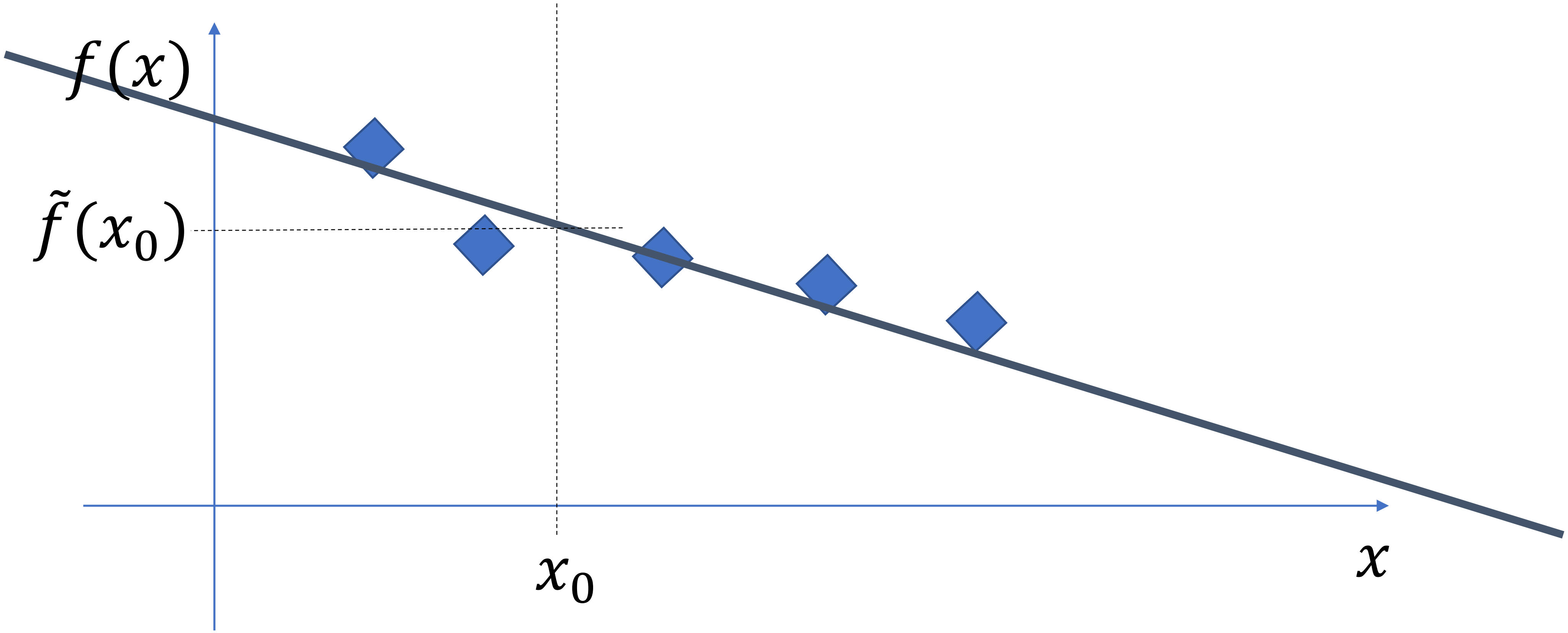

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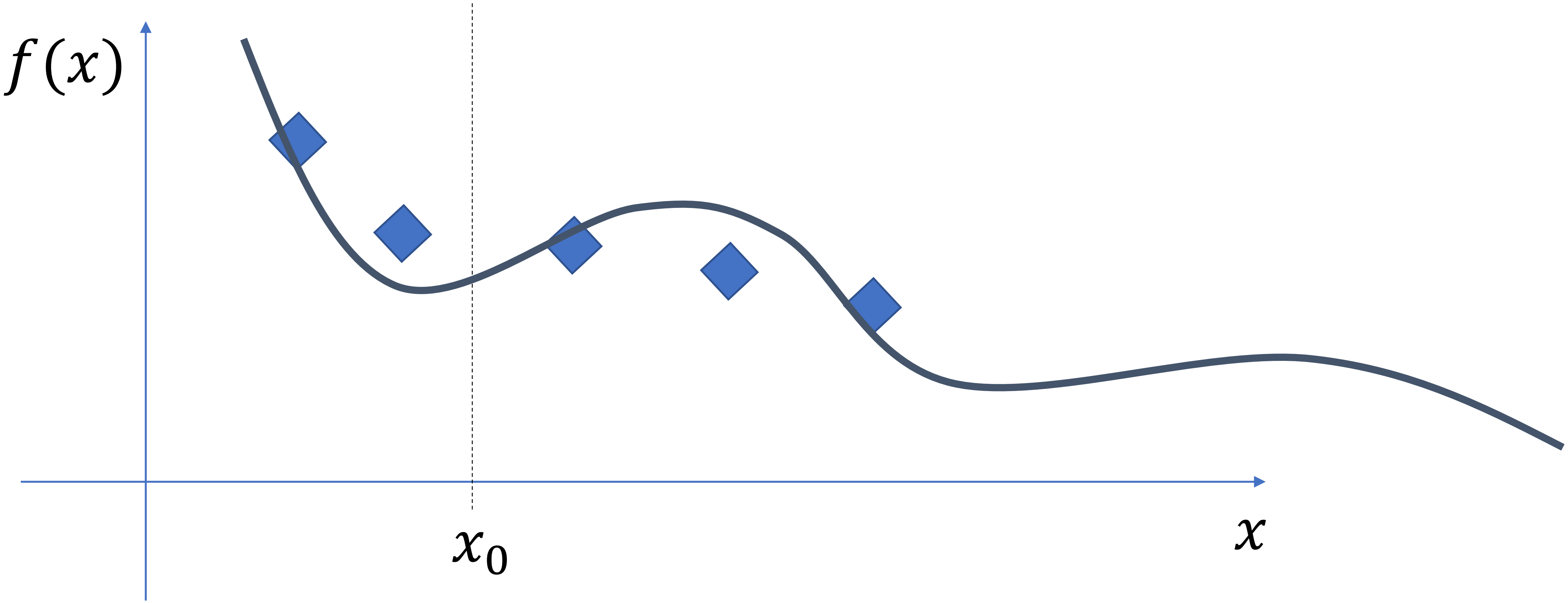

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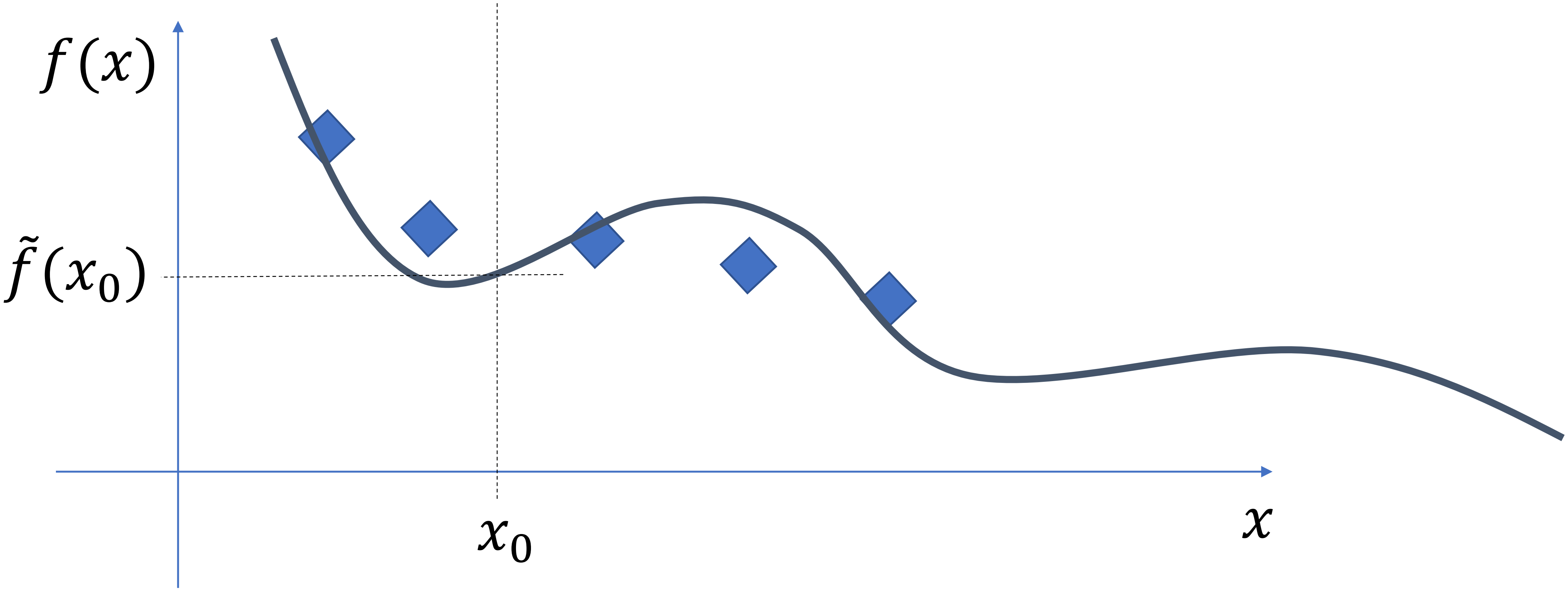

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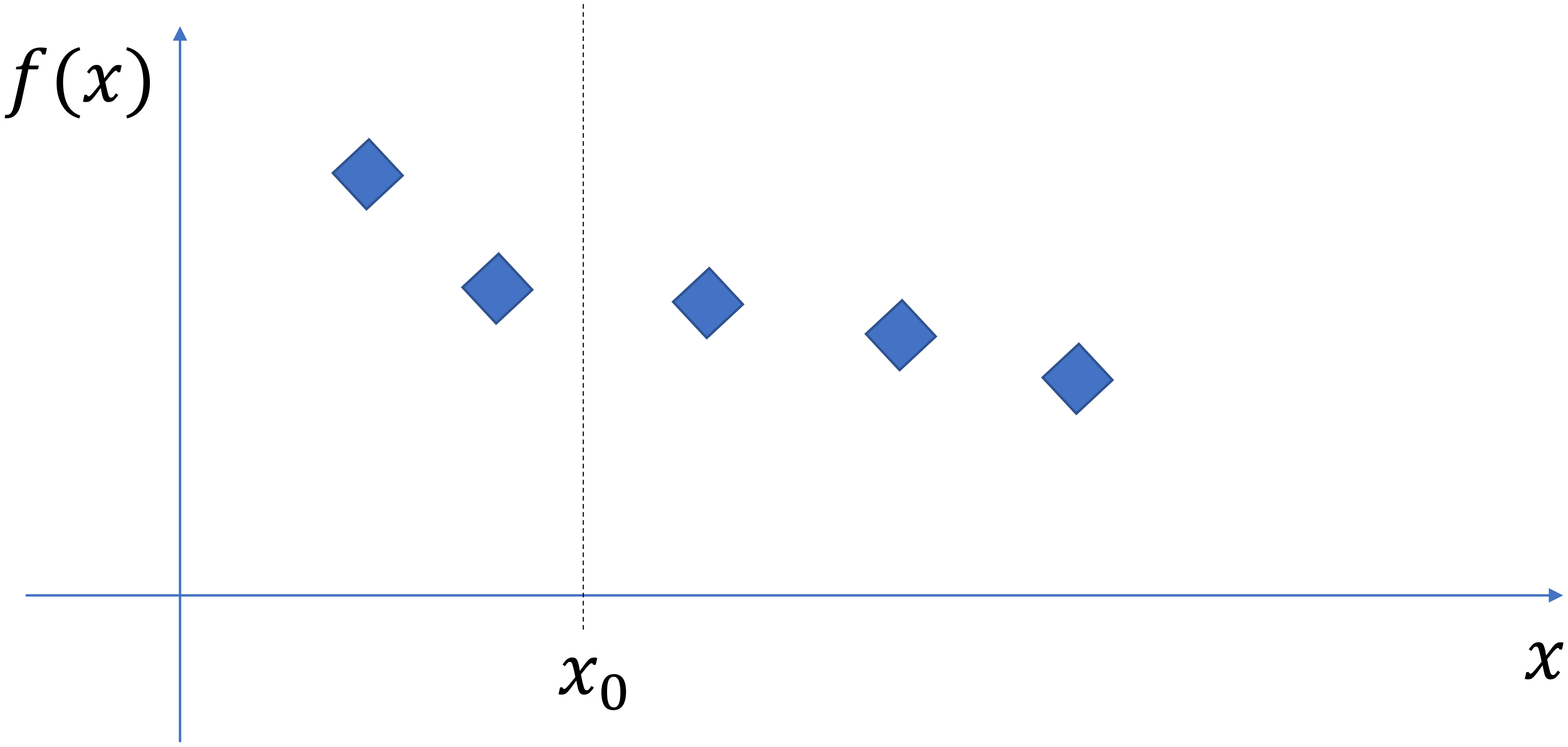
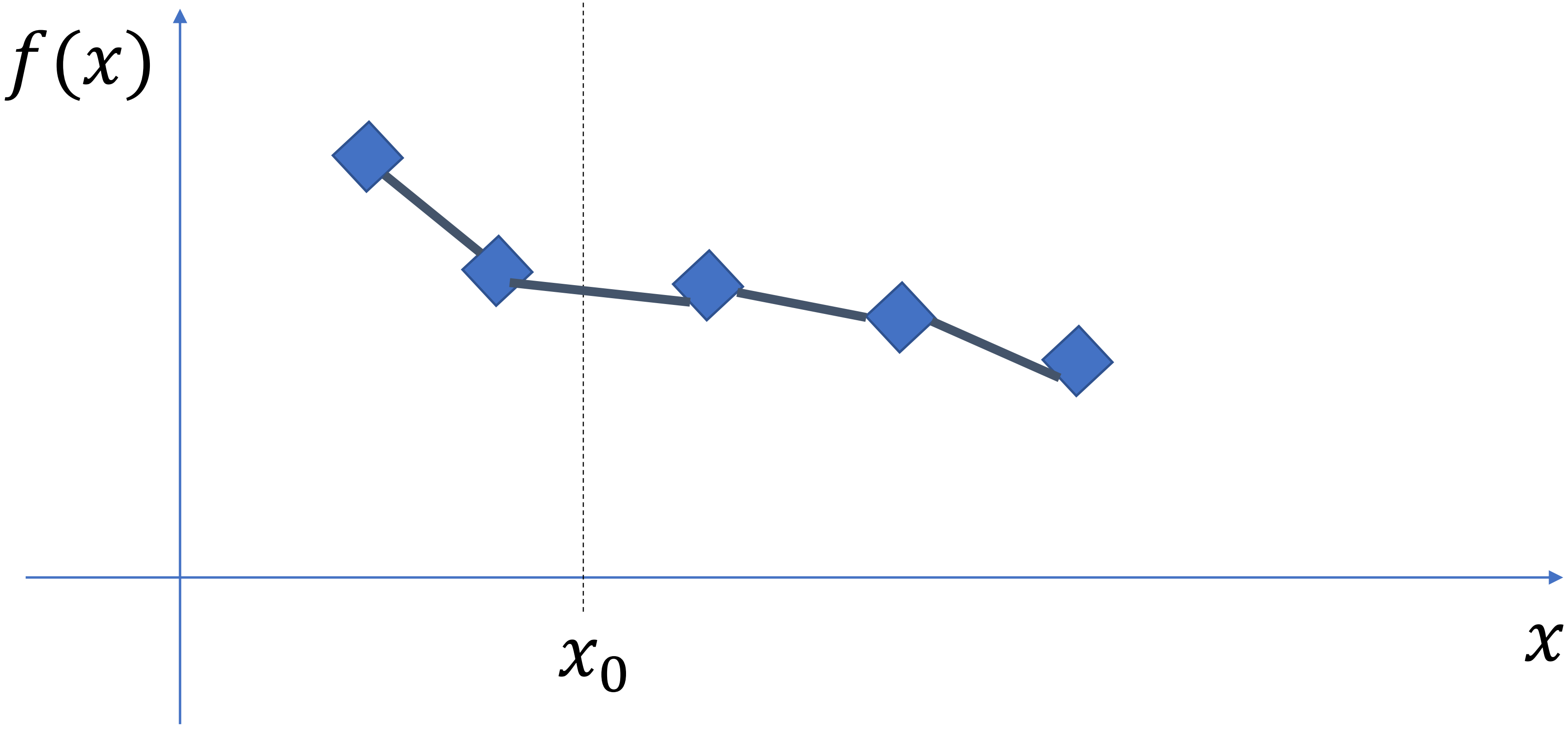


Interpolation



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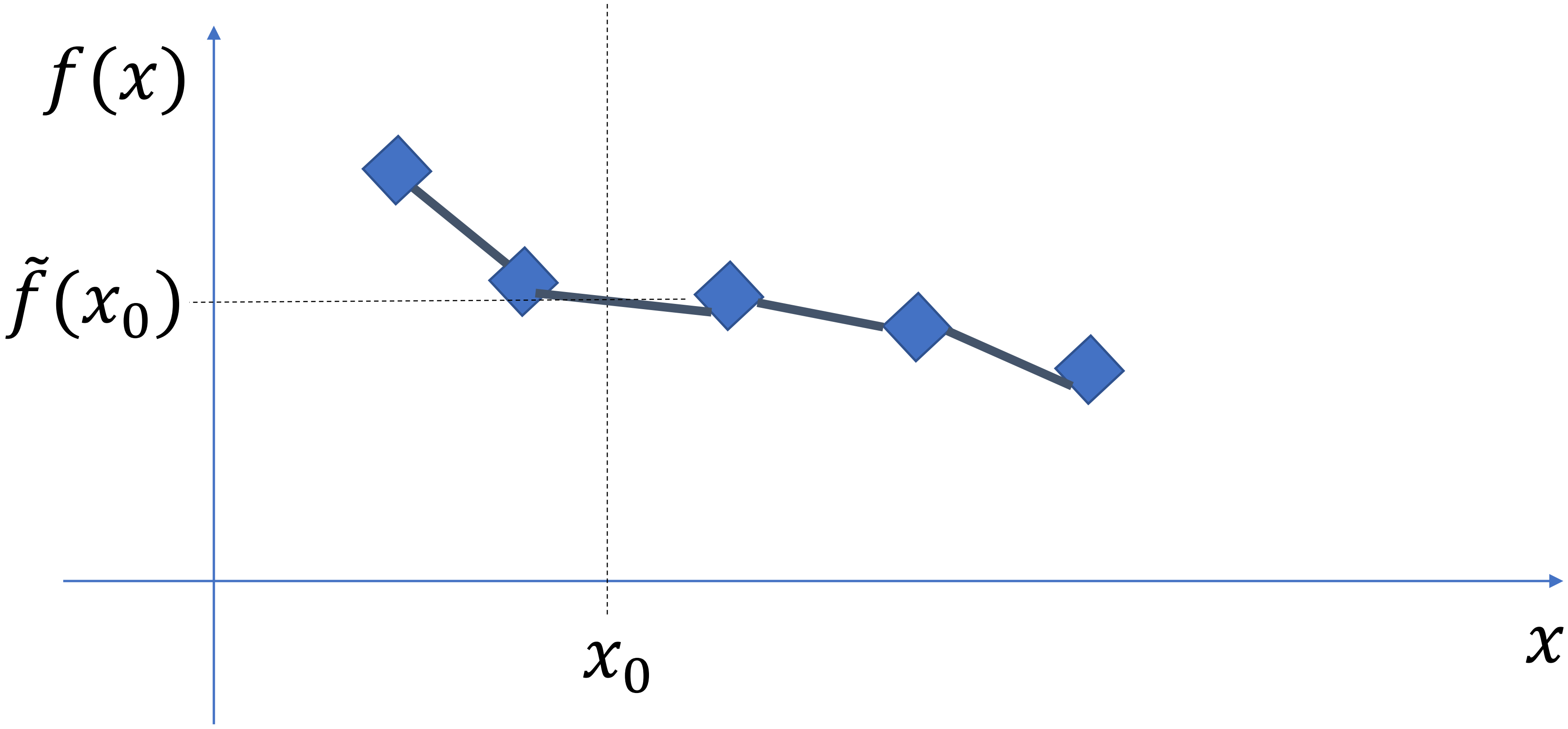

Tasks

- Typical tasks:
  - Classification
  - Regression (not the same as interpolation!)
- Further tasks:
  - Transcription

Transcription

- Speech to text

Transcription

- Speech to text

- Image to text

Vinyals, Oriol, et al. "Show and tell: A neural image caption generator."
Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.

Tasks

- Typical tasks:
  - Classification
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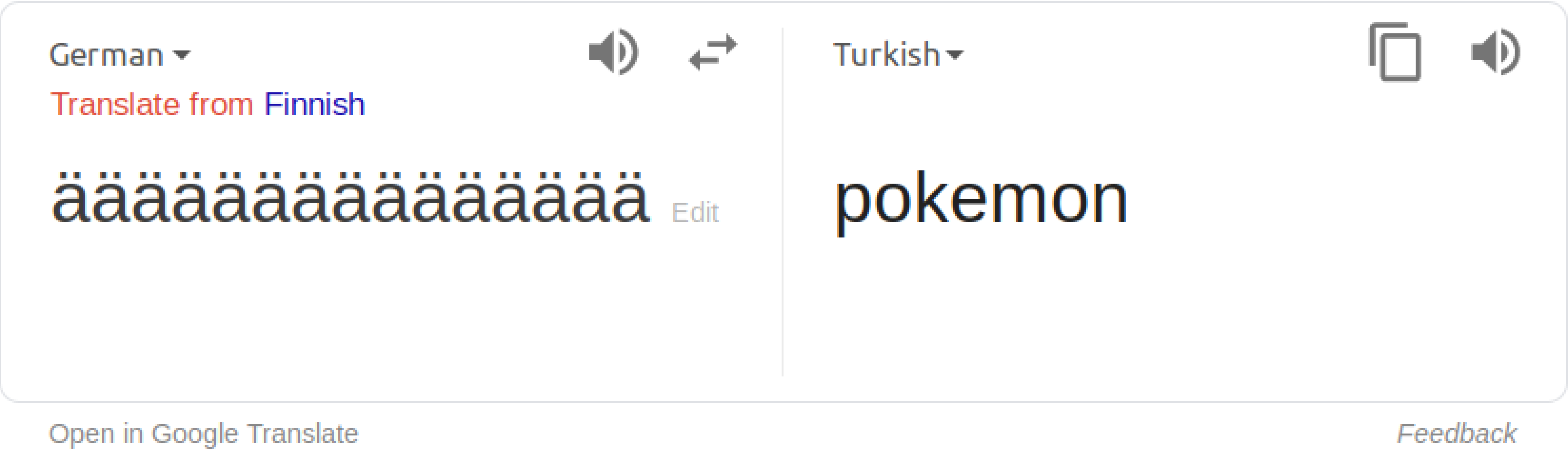
- Further tasks:
  - Transcription
  - Machine Translation

Machine Translation



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- Typical tasks:
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- Further tasks:
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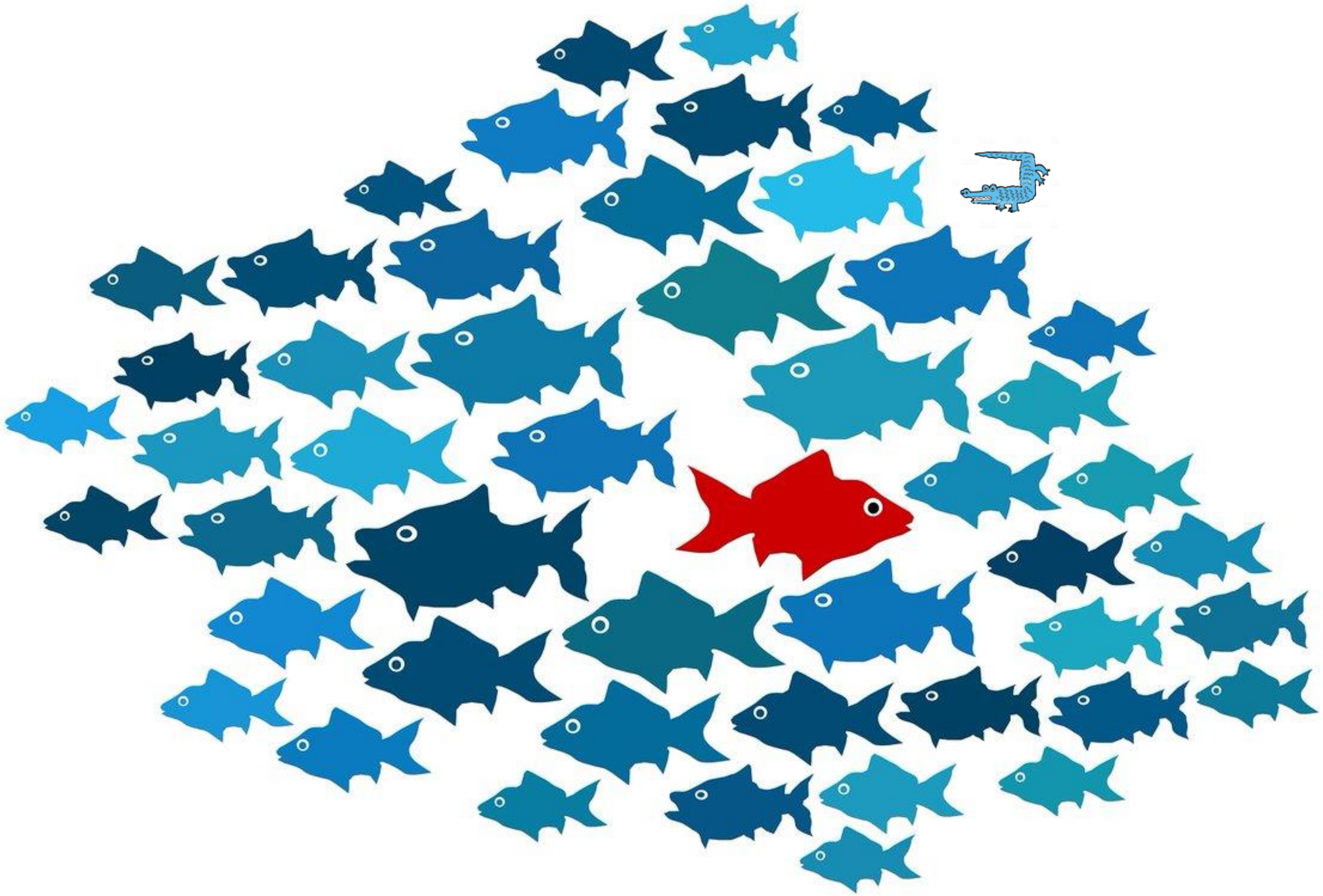
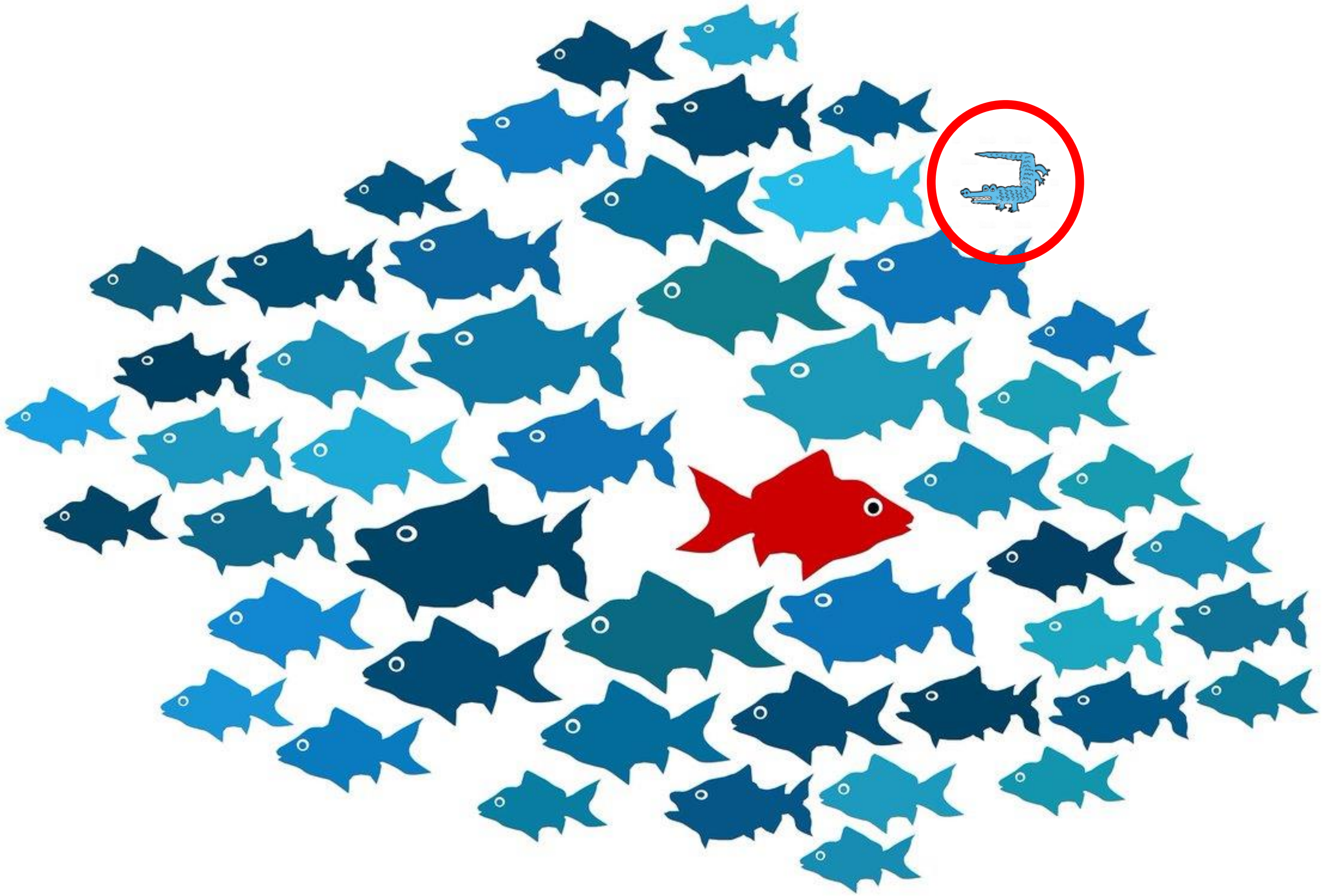
  - Machine Translation
  - Anomaly Detection

Anomaly Detection



https://towardsdatascience.com/a-brief-overview-of-outlier-detection-techniques-1e0b2c19e561

Anomaly Detection



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Tasks

- Typical tasks:
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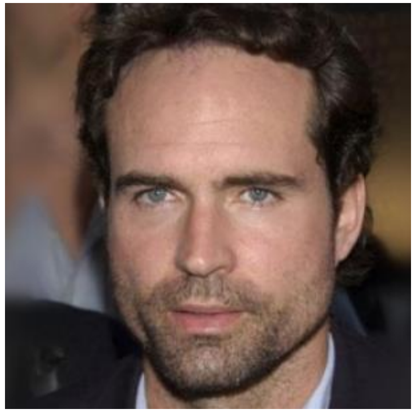
- Further tasks:
  - Transcription
  - Machine Translation
  - Anomaly Detection
  - Synthesis

Image Synthesis



A: Real

B: Fake

Karras, Tero, et al. "Progressive growing of gans for improved quality, stability, and variation." arXiv preprint arXiv:1710.10196 (2017).

Image Synthesis

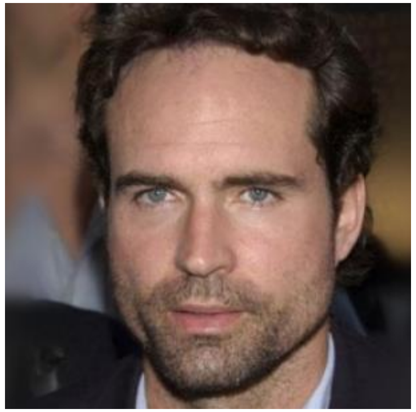


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Image Synthesis

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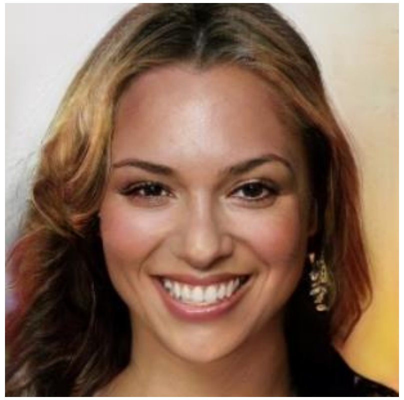

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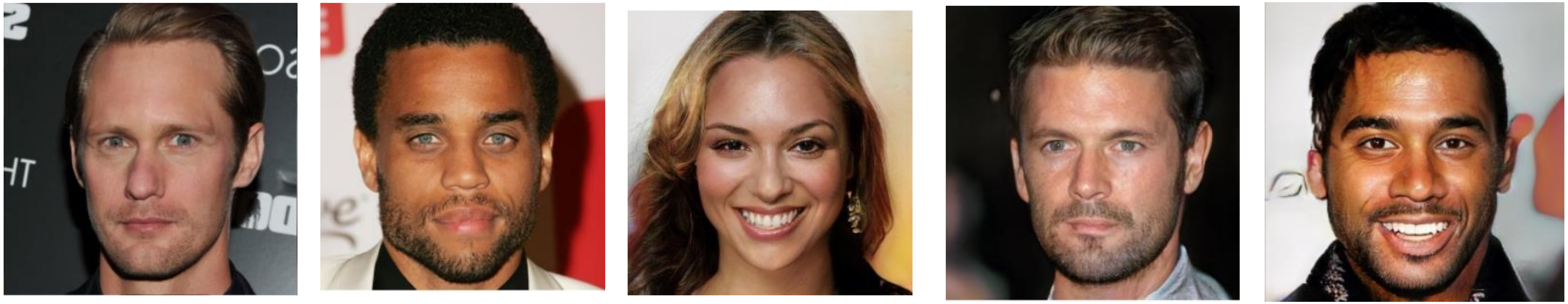

Real Real Fake Fake Fake

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Tasks

- Typical tasks:
  - Classification
  - Regression (not the same as interpolation!)
- Further tasks:
  - Transcription
  - Machine Translation
  - Anomaly Detection
  - Synthesis
  - Denoising
  - Imputation of missing values
  - Etc …

Scope of this course

- Basic/Fundamental Machine Learning methods and algorithms

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- Basic/Fundamental Machine Learning methods and algorithms
- Most tasks will be **classification** tasks

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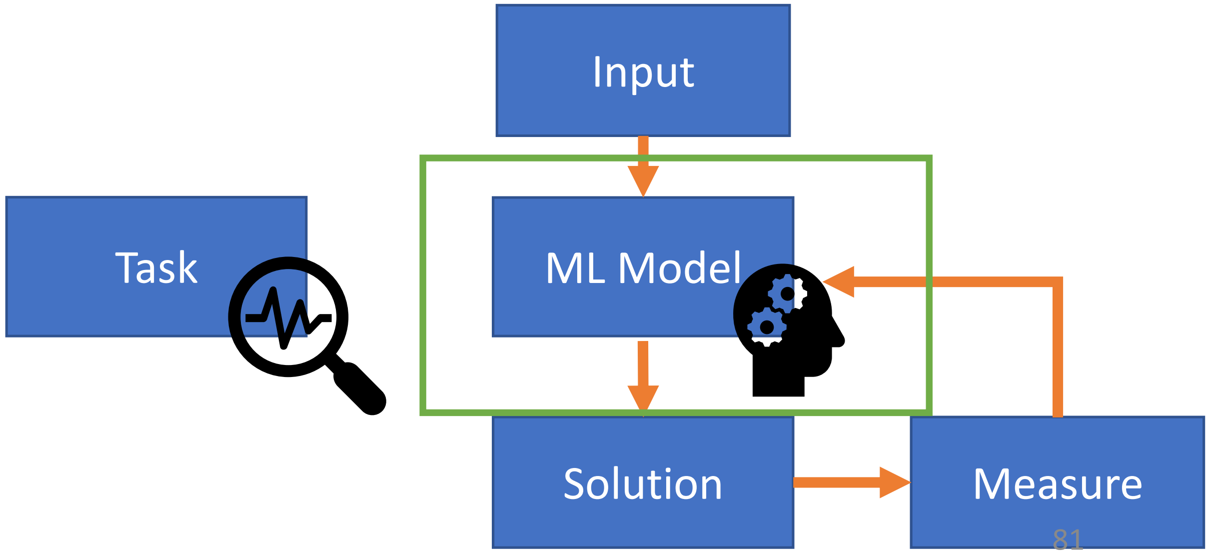

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- Machine Learning tasks
- <u>Broad types of Machine Learning Algorithms</u>
- How do input/output look like?
- Data partitioning

Broad types of ML Algorithms

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

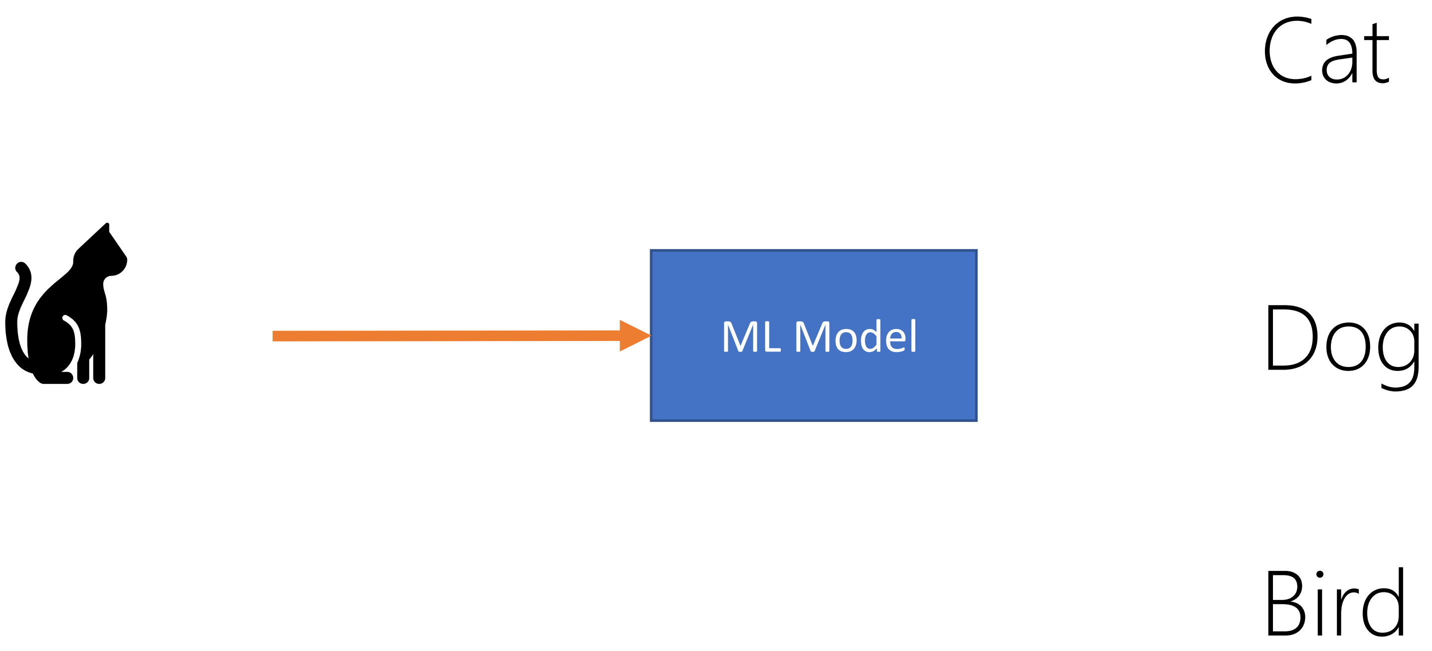
Supervised Learning

- Desired output is known!

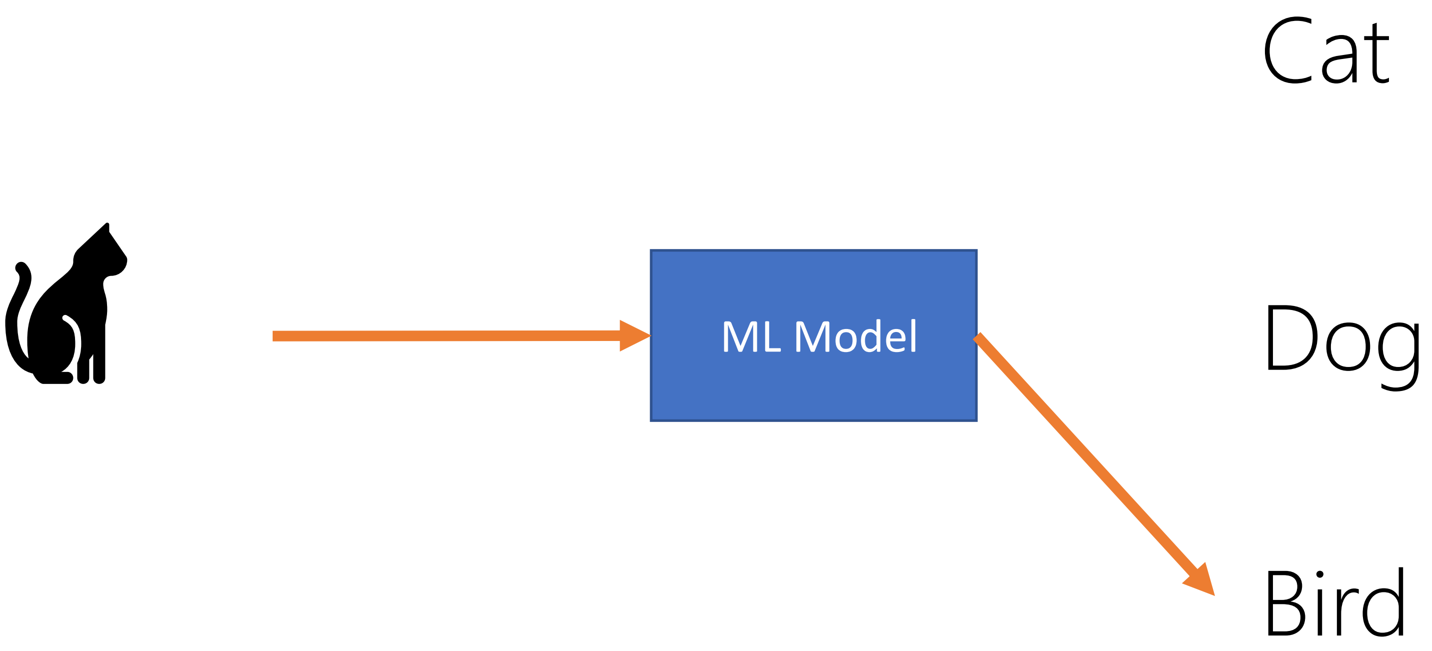
Supervised Learning

- Desired output is known!
- „teacher tells us right solution "

Classification



Classification



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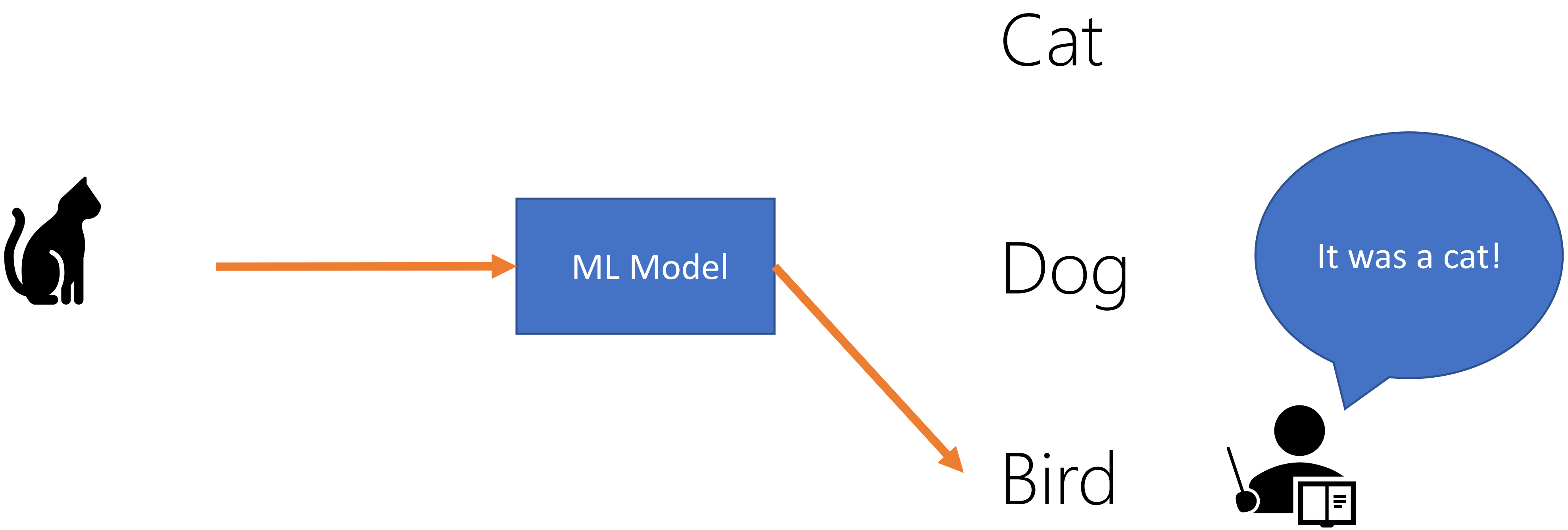

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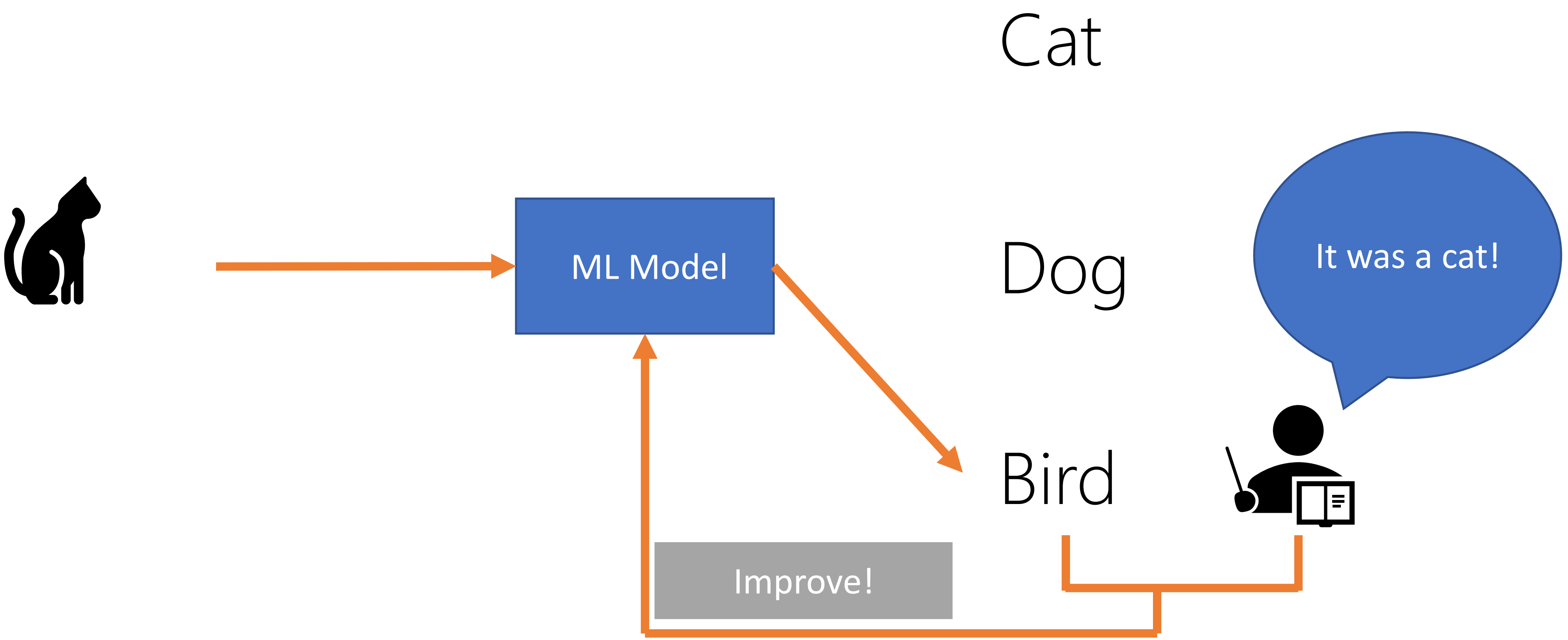
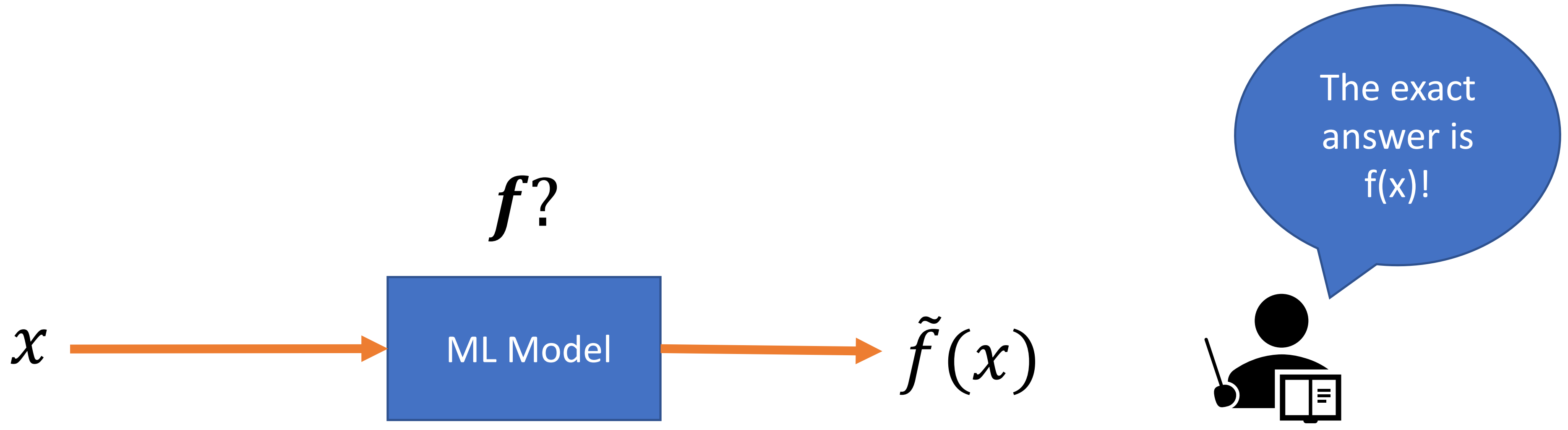
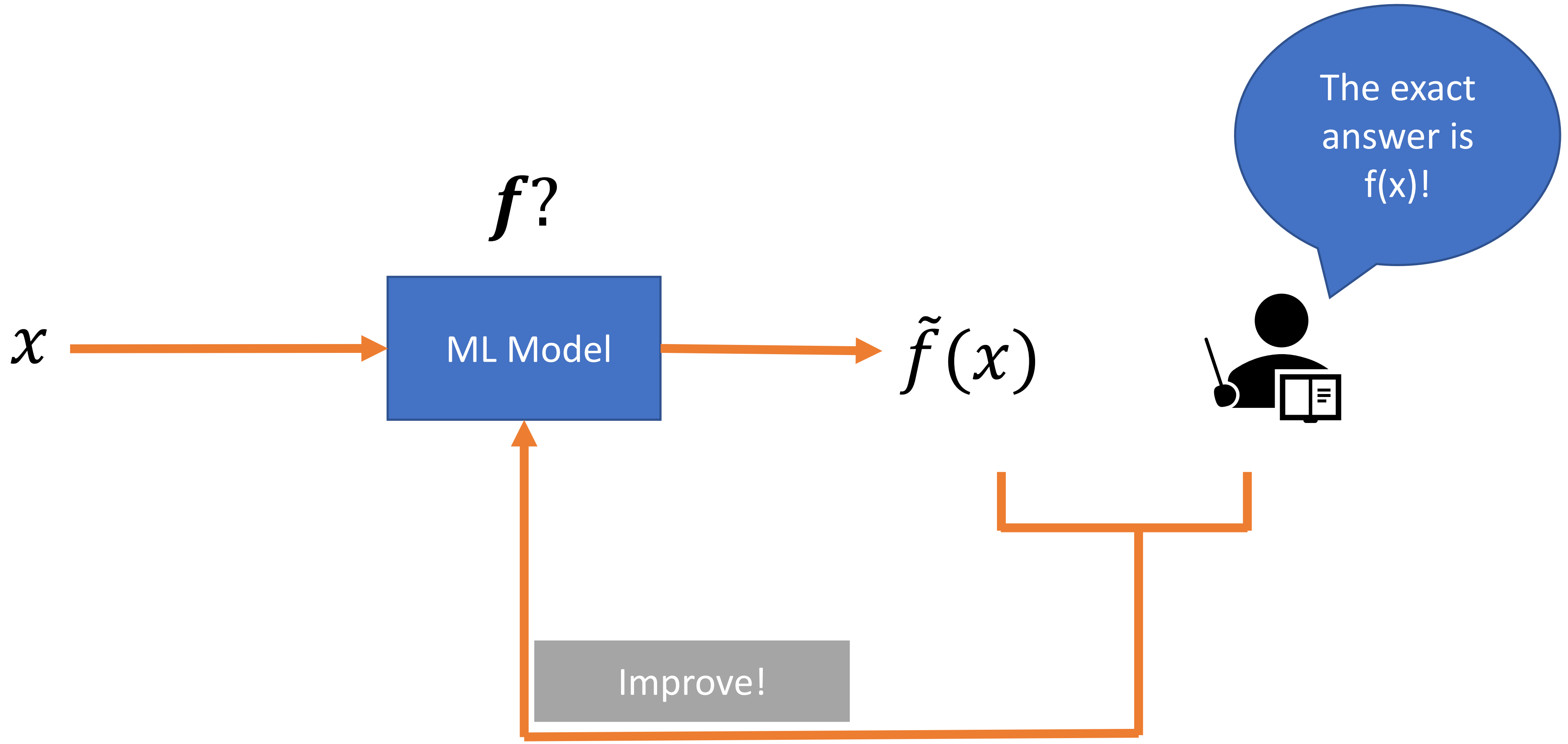


Regression

Regression



Regression



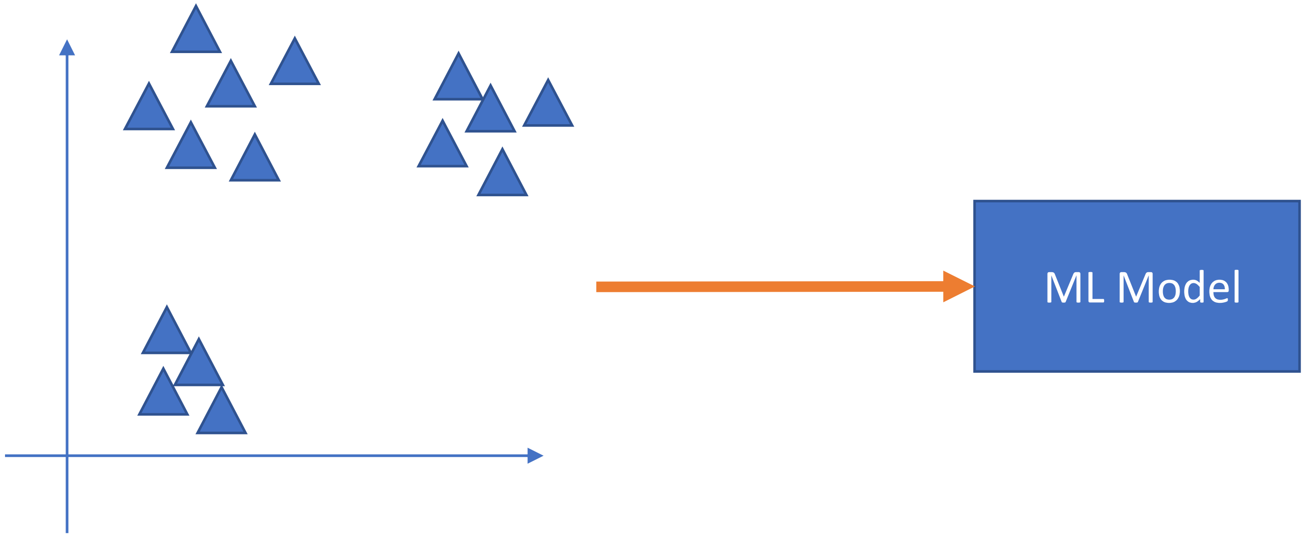
Unsupervised Learning

- Try to find useful properties/structures in example data set

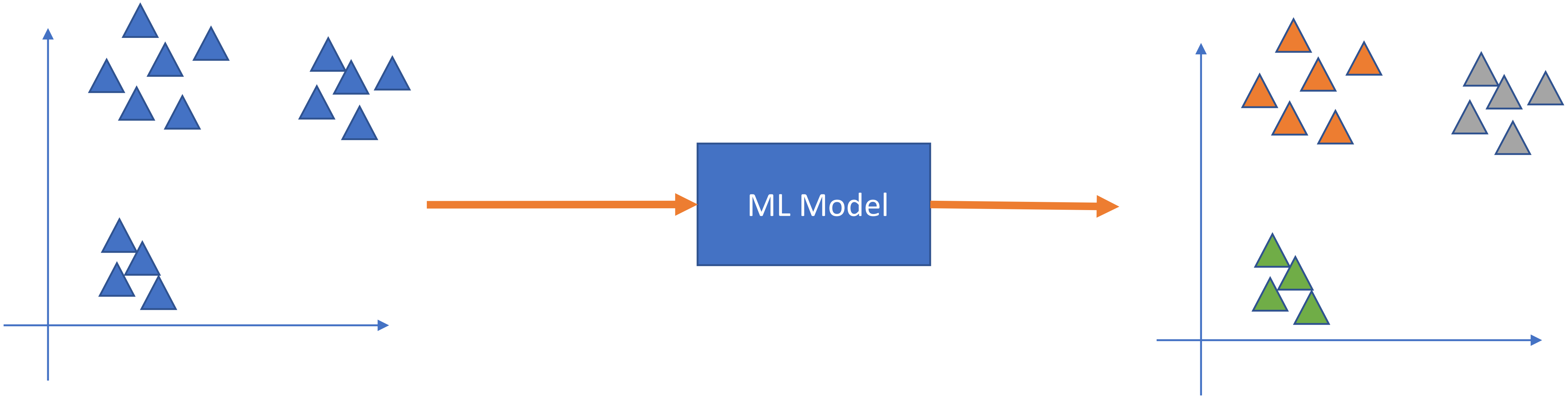
Unsupervised Learning

- Try to find useful properties/structures in example data set
- „no teacher "

Unsupervised learning



Unsupervised learning



Reinforcement Learning

- Learning by punishment / reward

Reinforcement Learning

- Learning by punishment / reward
- Feedback loop between learning system and environment

Reinforcement Learning

- Learning by punishment / reward
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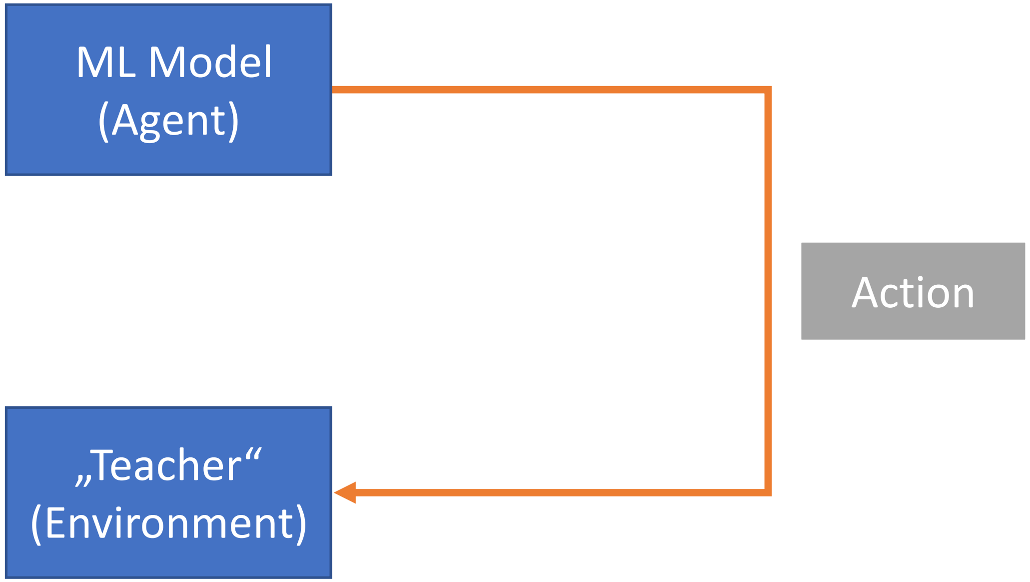
- „teacher points to right direction“

Reinforcement Learning

ML Model
(Agent)

„Teacher“
(Environment)

Reinforcement Learning



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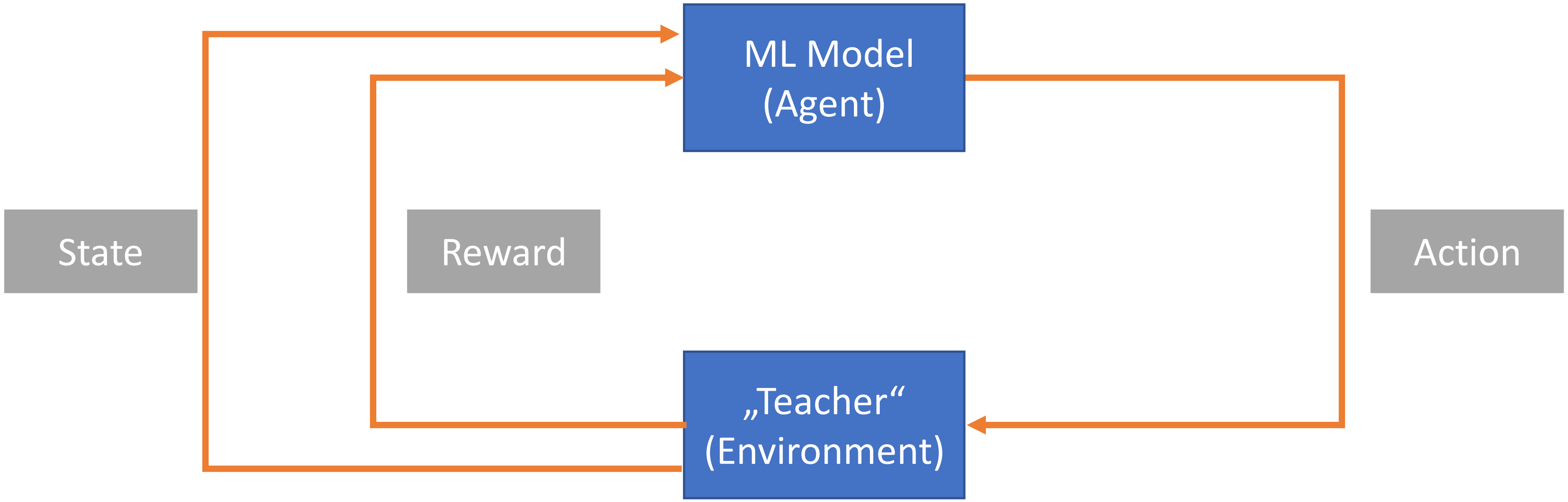

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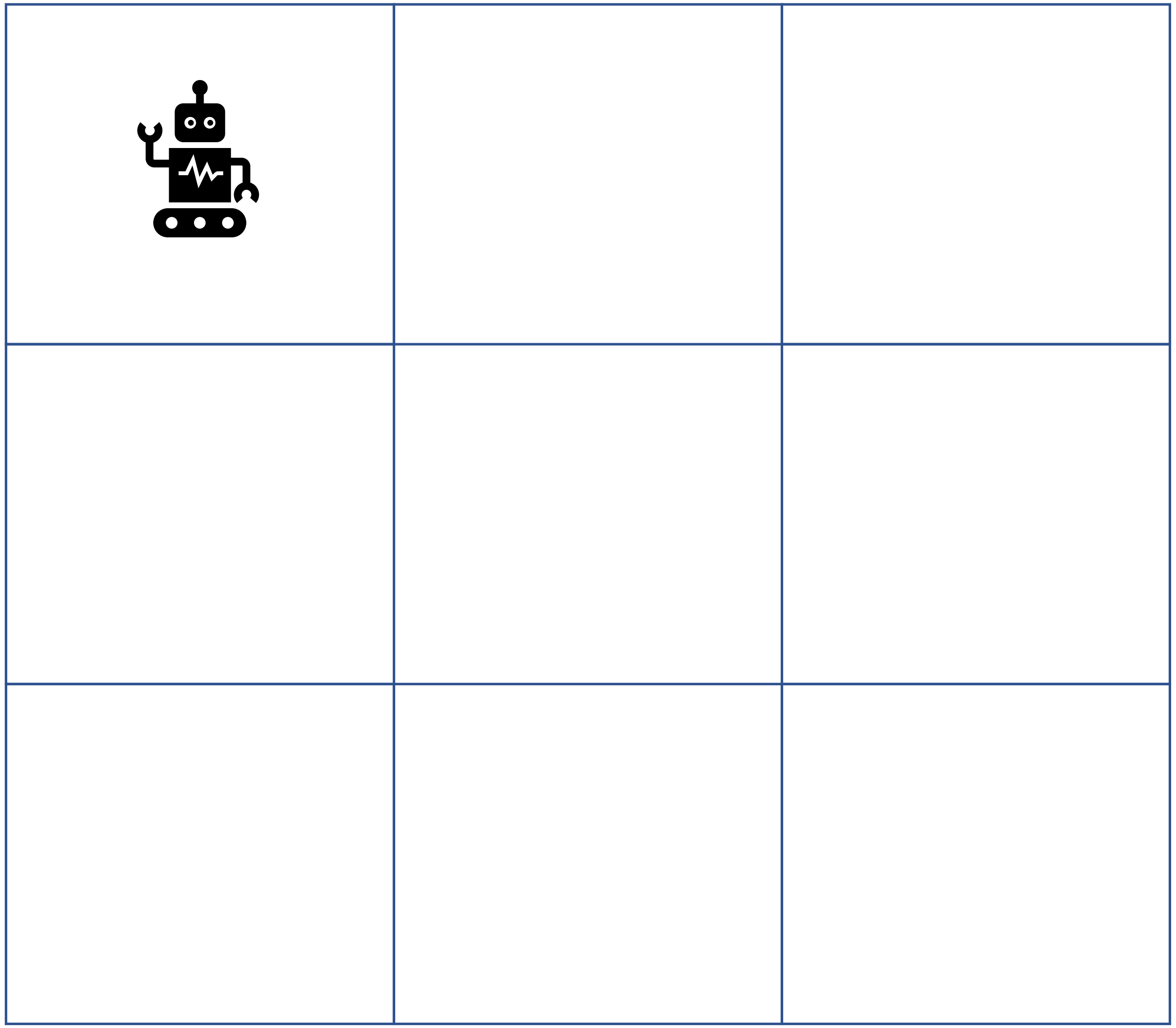

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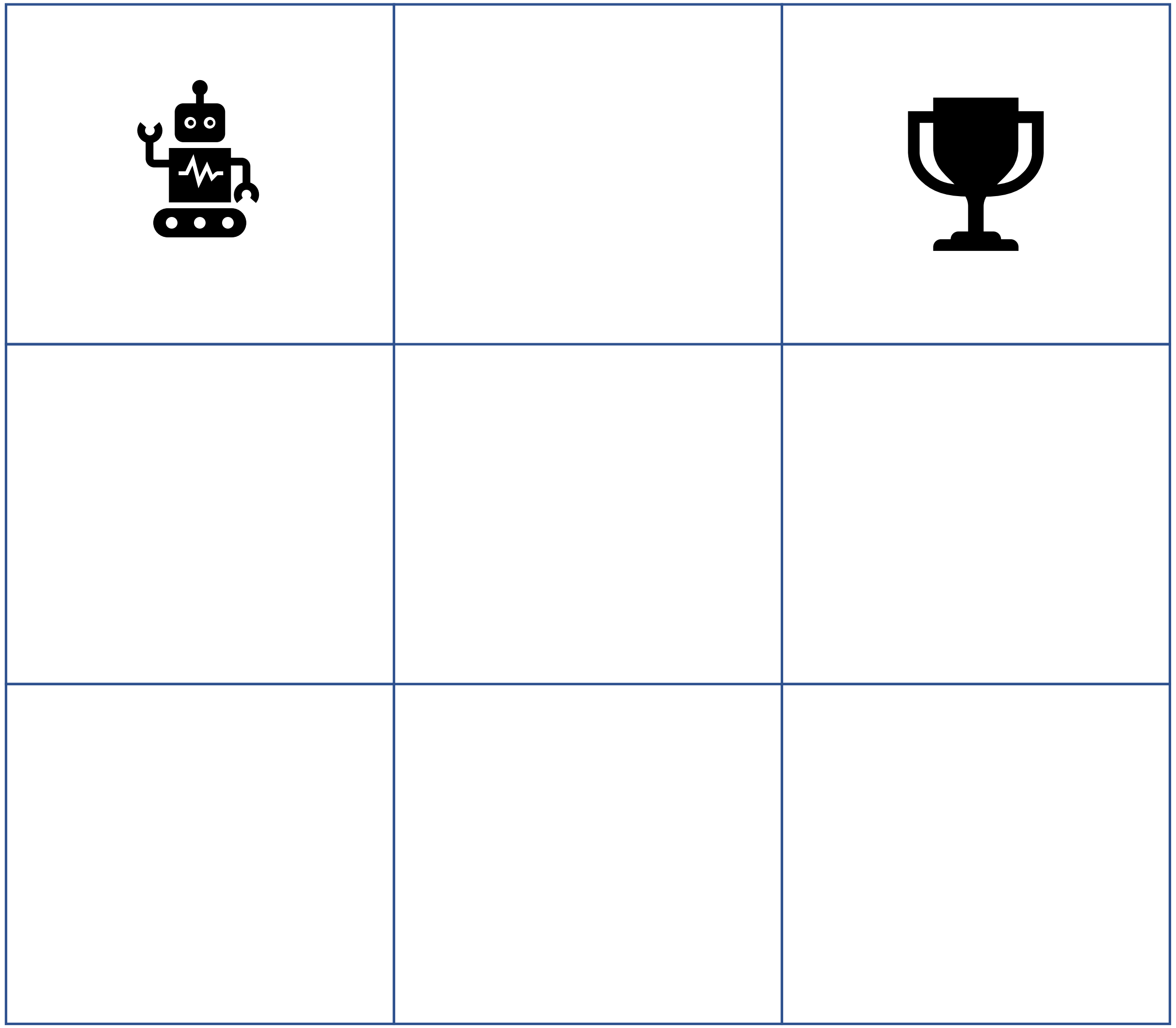

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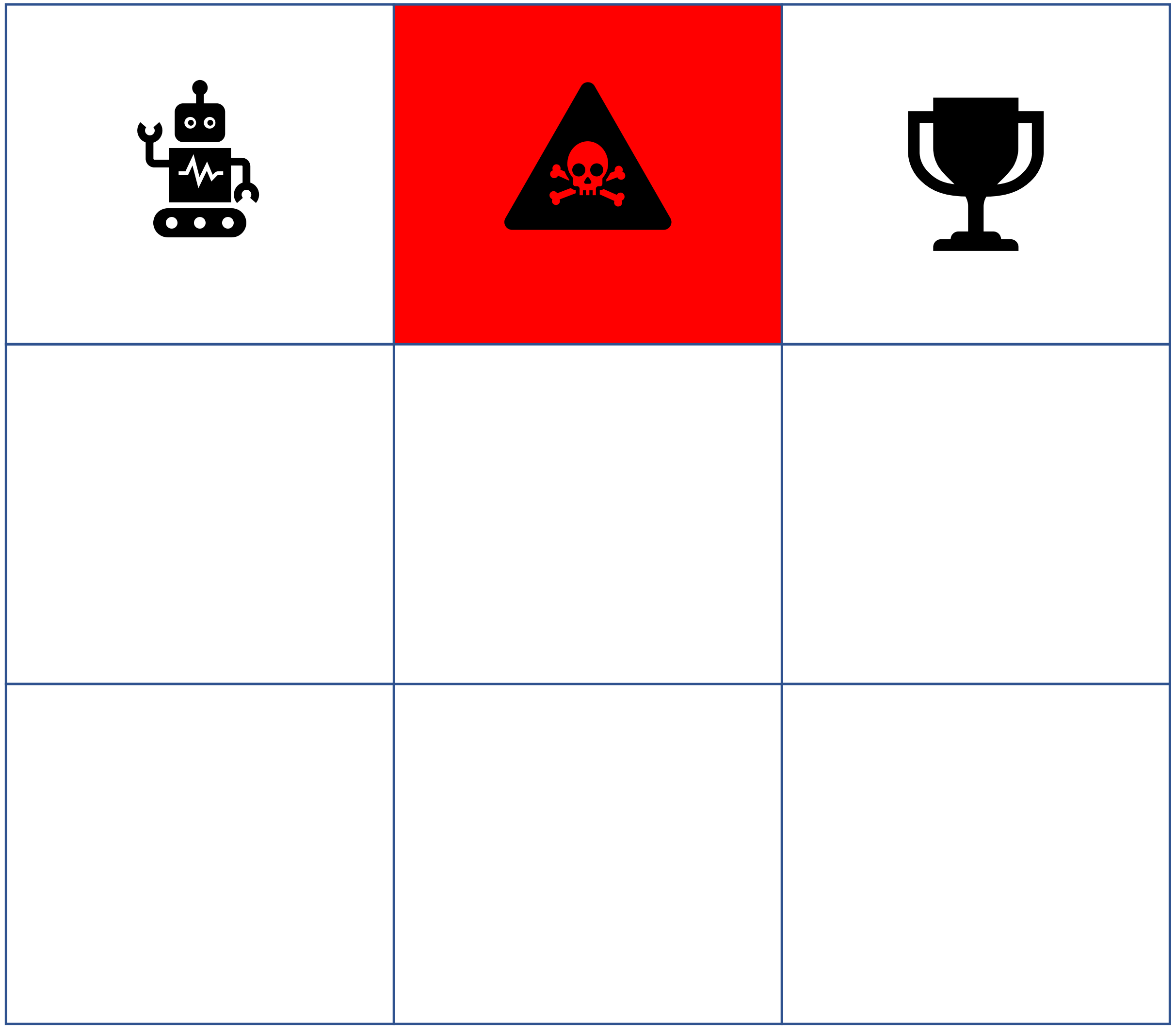

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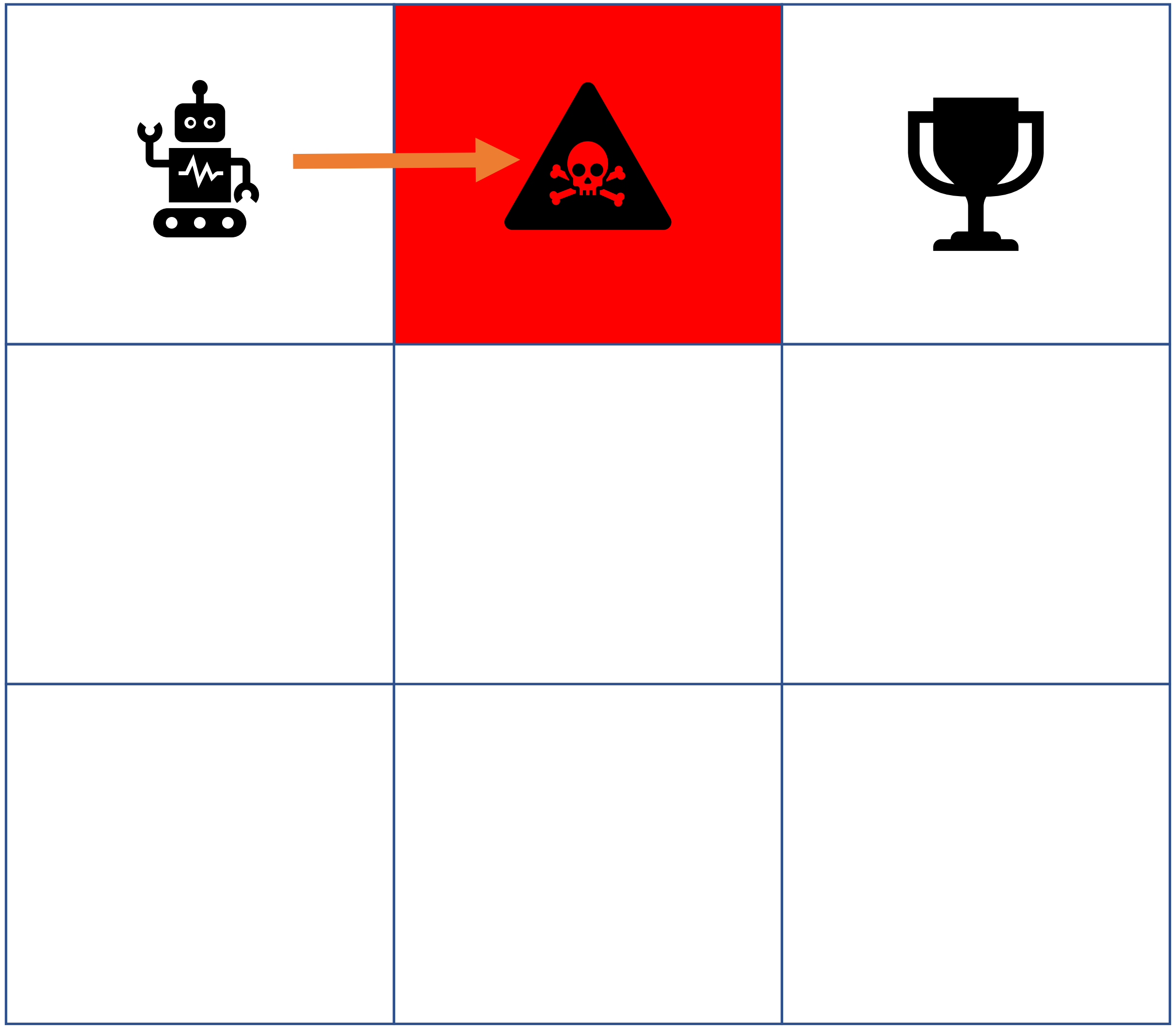

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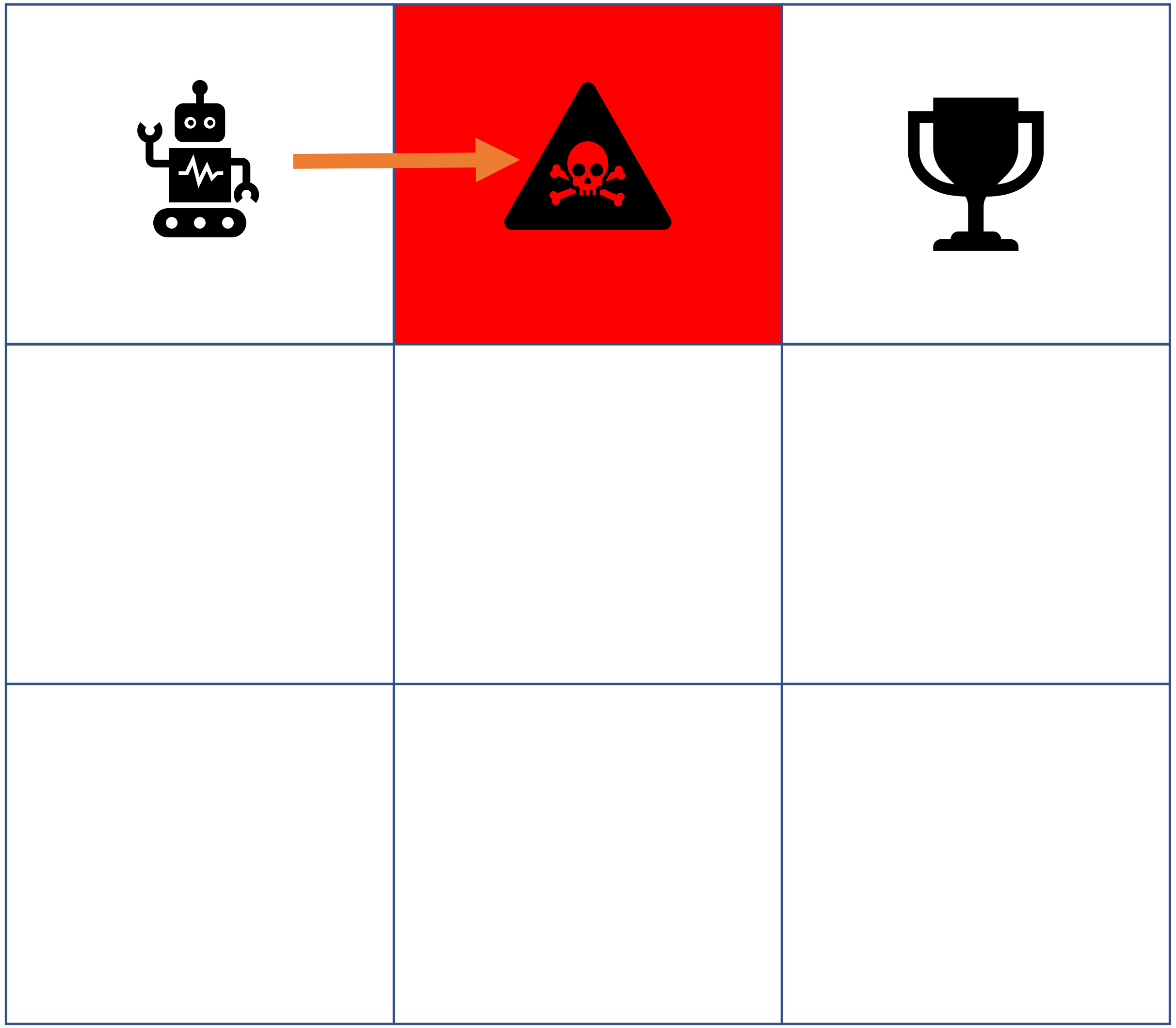

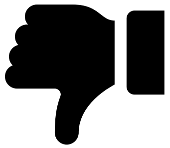

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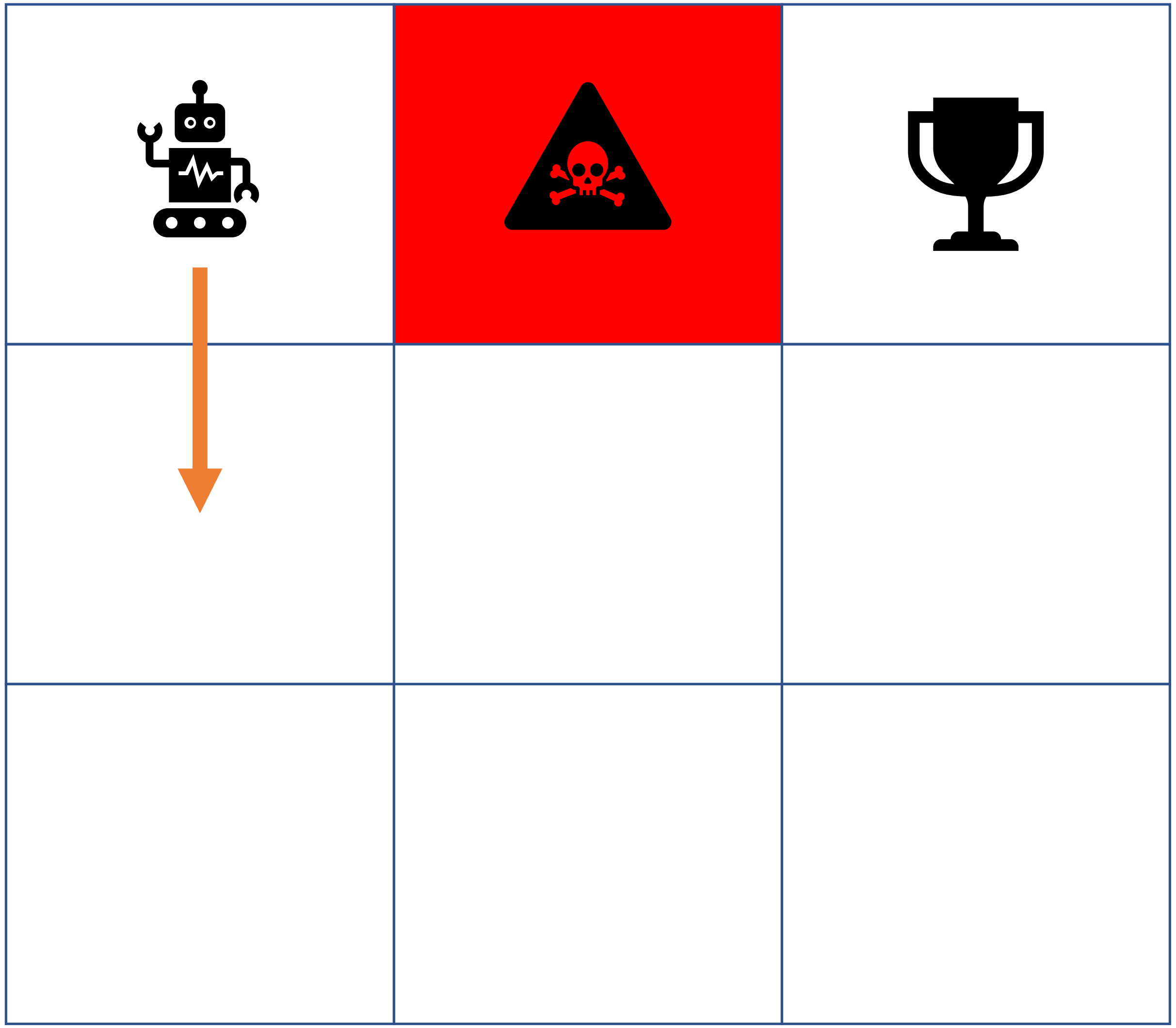

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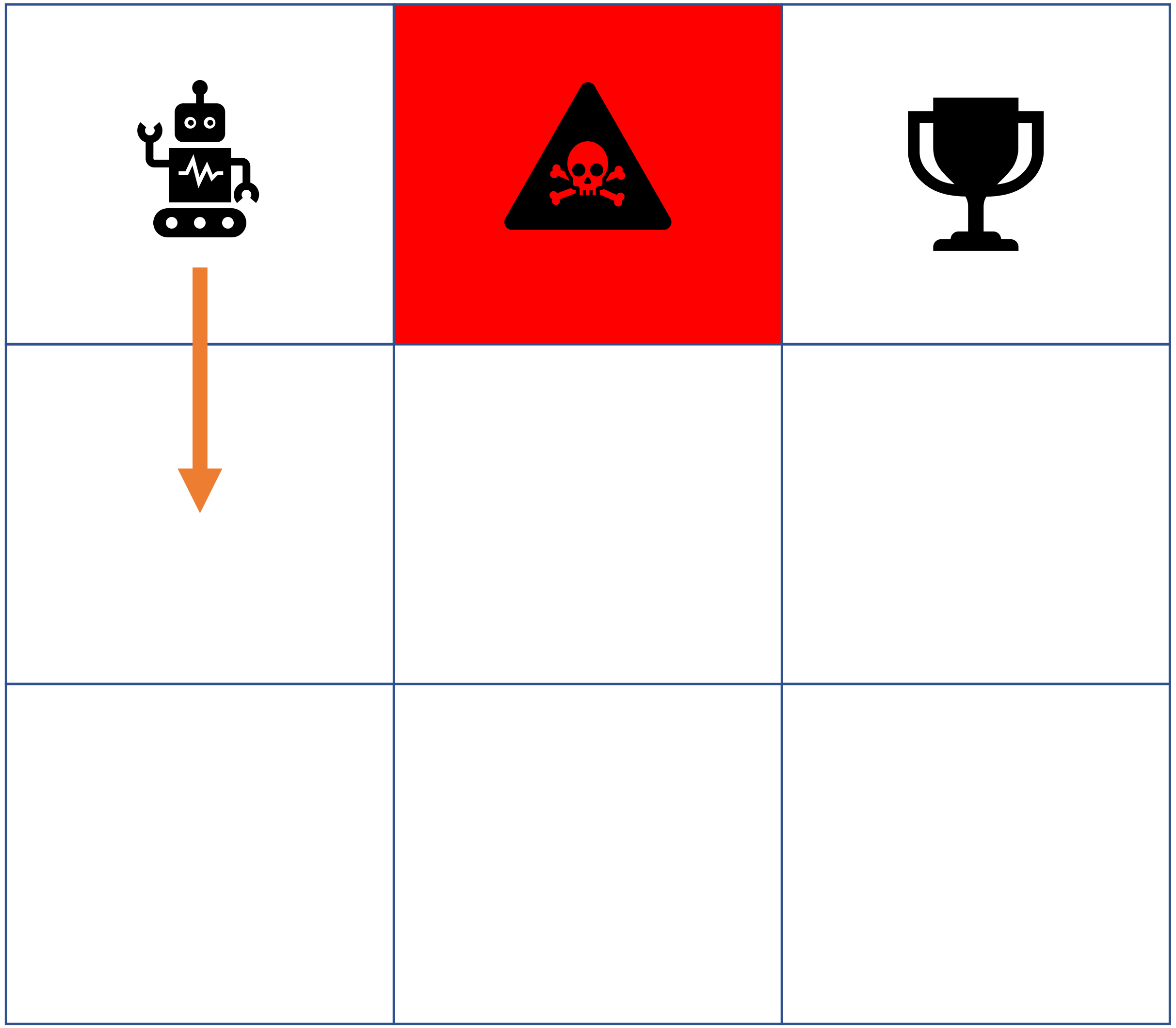

Reinforcement Learning

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Reinforcement Learning

- Learning by punishment / reward
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- A little more complicated than illustration ;)
- More details in Computer Robot Systems

Content

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- When does a Machine learn?
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When does a Machine learn?

Mitchell (1997):
„A computer is said to learn from experience E*,*
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0. Define task T
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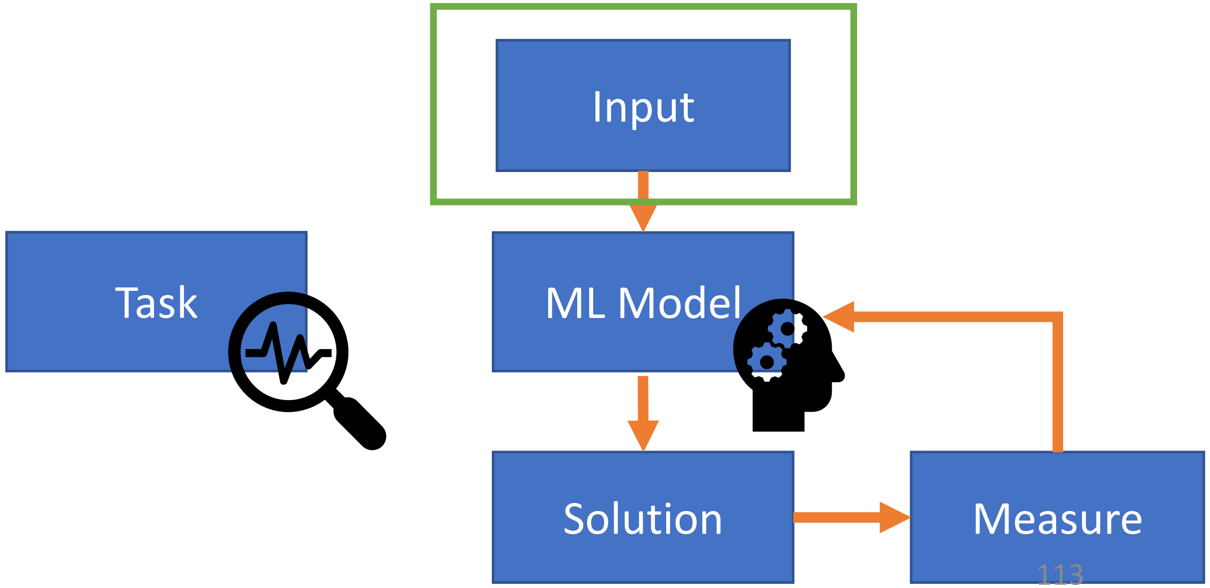

What does the input look like?

- Usually a vector $x \epsilon R^N$

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- Either raw observation vector

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- Usually a vector $x \epsilon R^N$
- Either raw observation vector
- or feature vector,
  where each component may represent a specific feature

What are features?

- Salient properties of observation

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- In generable measurable

What are features?

- Salient properties of observation
- In generable measurable
- Sometimes needs to be extracted from observation

Example: Disease diagnosis

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- Possible features (can be observed):

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  - Oxygen partial pressure in blood

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  - Etc …

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- Possible features (can be observed):
  - Oxygen partial pressure in blood
  - Carbon dioxide partial pressure
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$$x = \begin{pmatrix} heart\,rate \\ blood\,pressure \\ \dots \\ nose\,length \end{pmatrix}$$

Example: Iris classification

- Raw observation: image

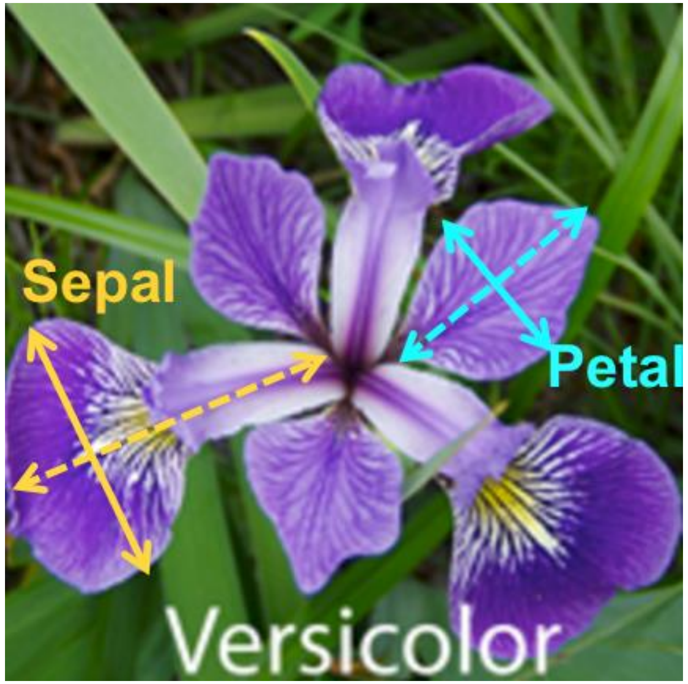
Iris setosa

Iris versicolor

Iris virginica

Example: Iris classification

- (Manually) extracted features from image:



$$x = \begin{pmatrix} sepal\ length \\ \vdots \\ petal\ width \end{pmatrix}$$

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[[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
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First sample

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```

Second sample

Example: Iris classification

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- Example:

```
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```

Third sample

Example: Iris classification

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- Example:

Sepal length

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[[5.1 3.5 1.4 0.2]
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```

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Sepal width

```
[[5.1 3.5 1.4 0.2]
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Petal length

```
[[5.1 3.5 1.4 0.2]
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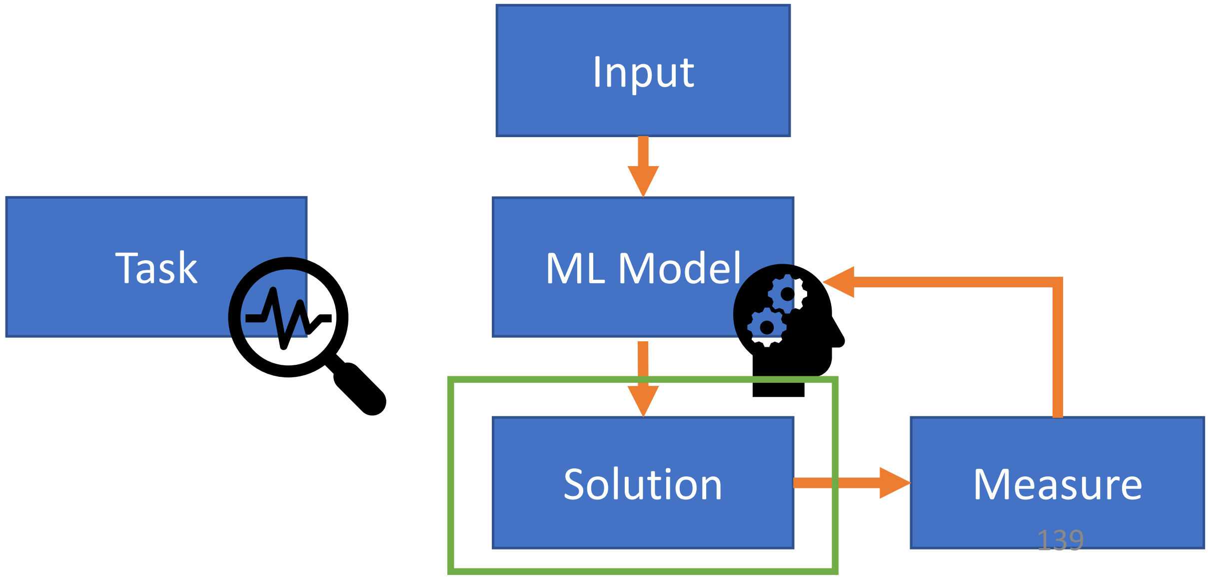
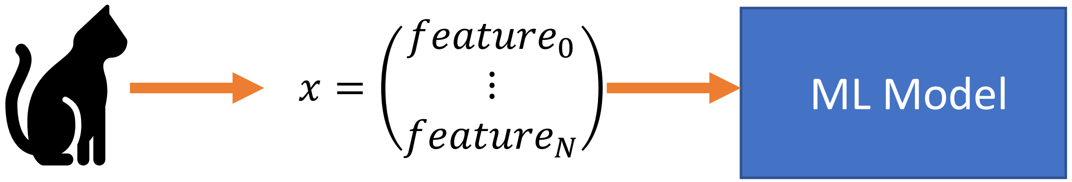


How does the output look like?

- For supervised classification (categorical output):



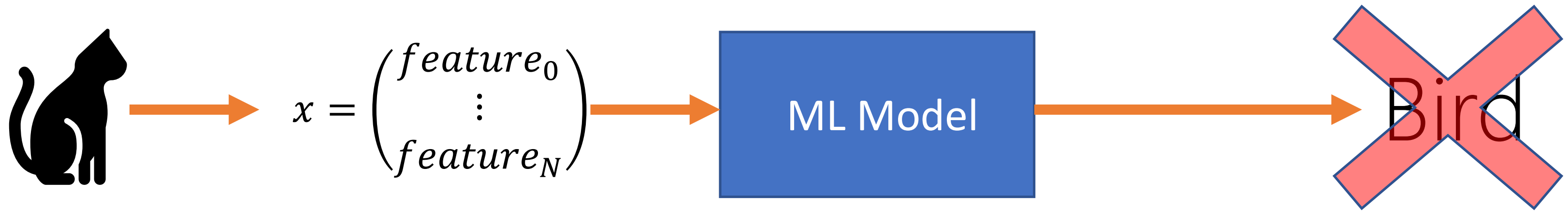
How does the output look like?

- For supervised classification (categorical output):

 $\rightarrow$ $x = \begin{pmatrix} feature_0 \\ \vdots \\ feature_N \end{pmatrix}$ $\rightarrow$ ML Model $\rightarrow$ Bird

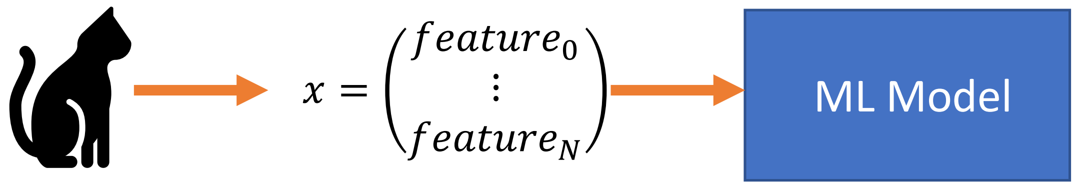
How does the output look like?

- For supervised classification (categorical output)



How does the output look like?

- For supervised classification (categorical output):
- Numerical class labels!



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$$x = \begin{pmatrix} feature_0 \\ \vdots \\ feature_N \end{pmatrix} \rightarrow \boxed{\text{ML Model}} \rightarrow 0$$

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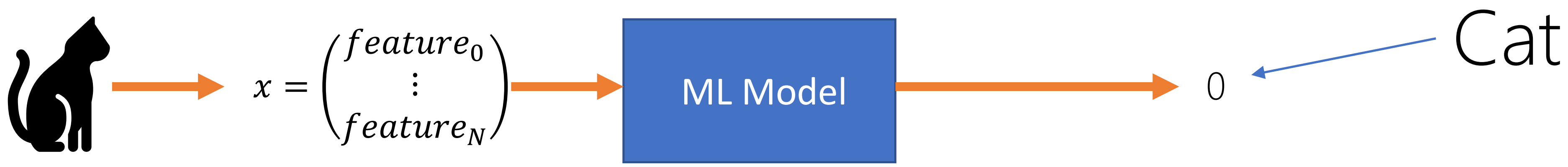

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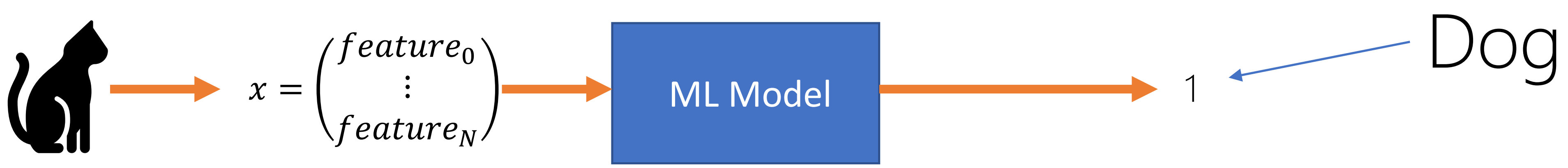

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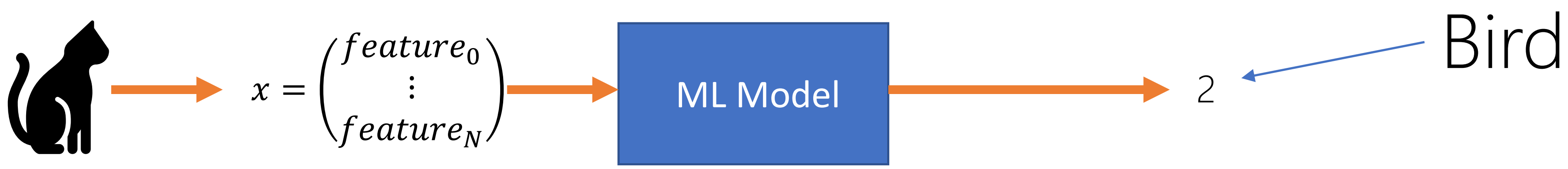

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$$x = \begin{pmatrix} feature_0 \\ \vdots \\ feature_N \end{pmatrix}$$

ML Model

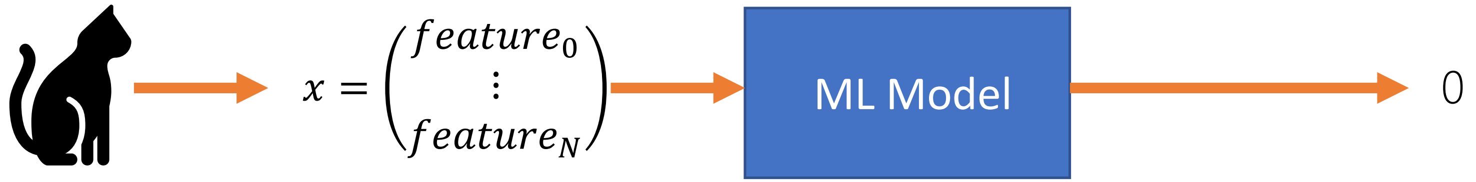
2

Bird

Rather uncommon for multi-class tasks!

How does the output look like?

- For supervised classification (categorical output):
- Numerical class labels!
- More common for binary classification



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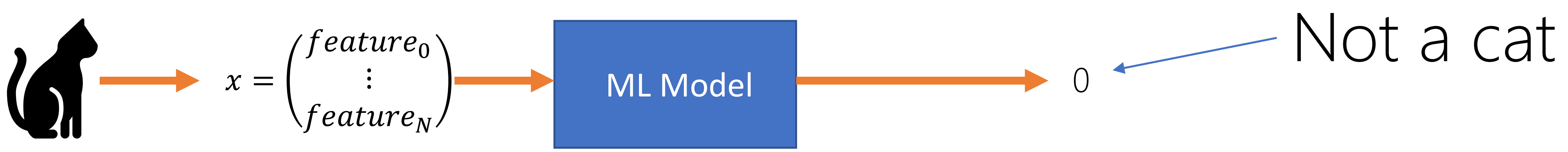

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$$x = \begin{pmatrix} feature_0 \\ \vdots \\ feature_N \end{pmatrix} \rightarrow \boxed{\text{ML Model}} \longrightarrow 1$$

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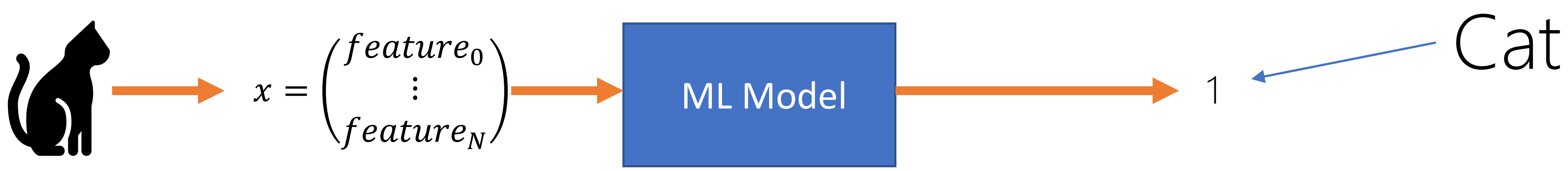

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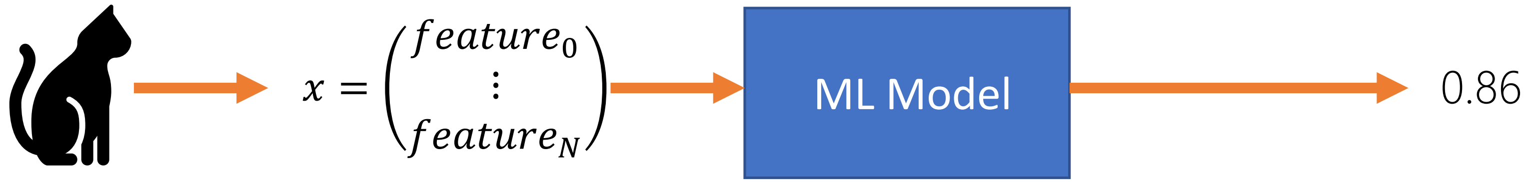

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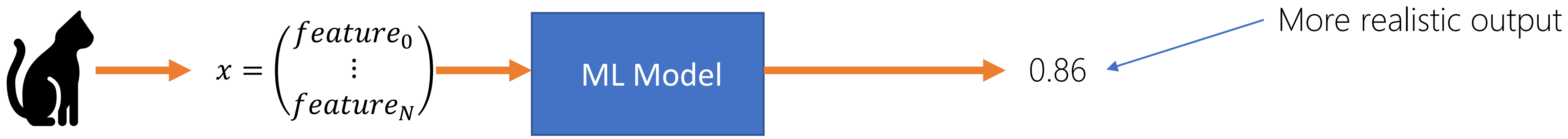

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- For supervised classification (categorical output):
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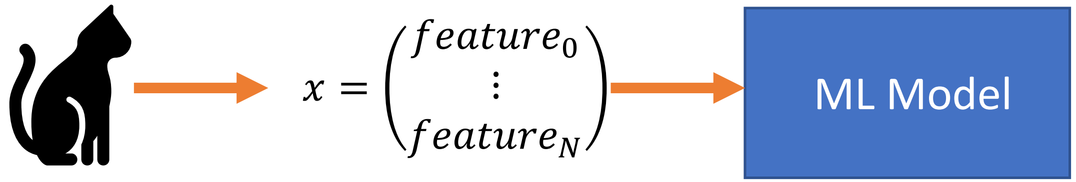

How does the output look like?

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$$x = \begin{pmatrix} feature_0 \\ \vdots \\ feature_N \end{pmatrix} \rightarrow \boxed{\text{ML Model}} \rightarrow \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

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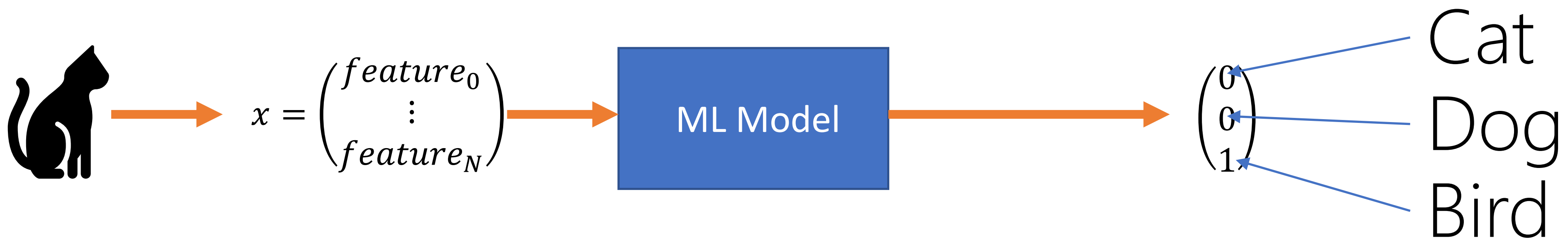

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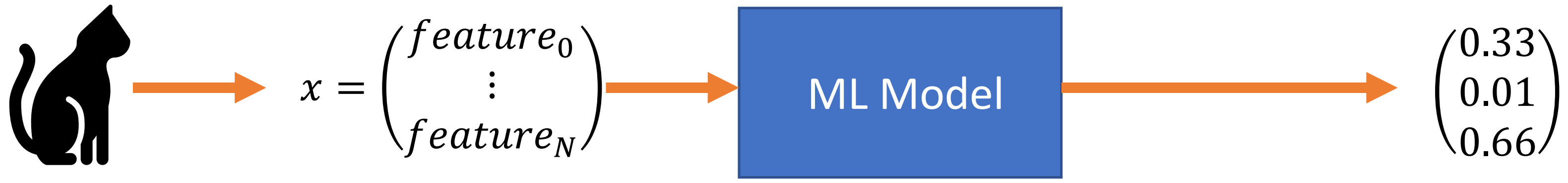

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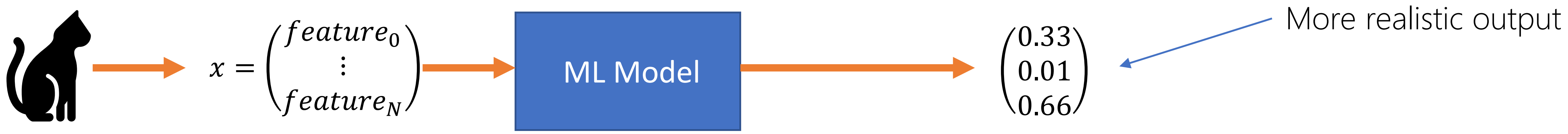

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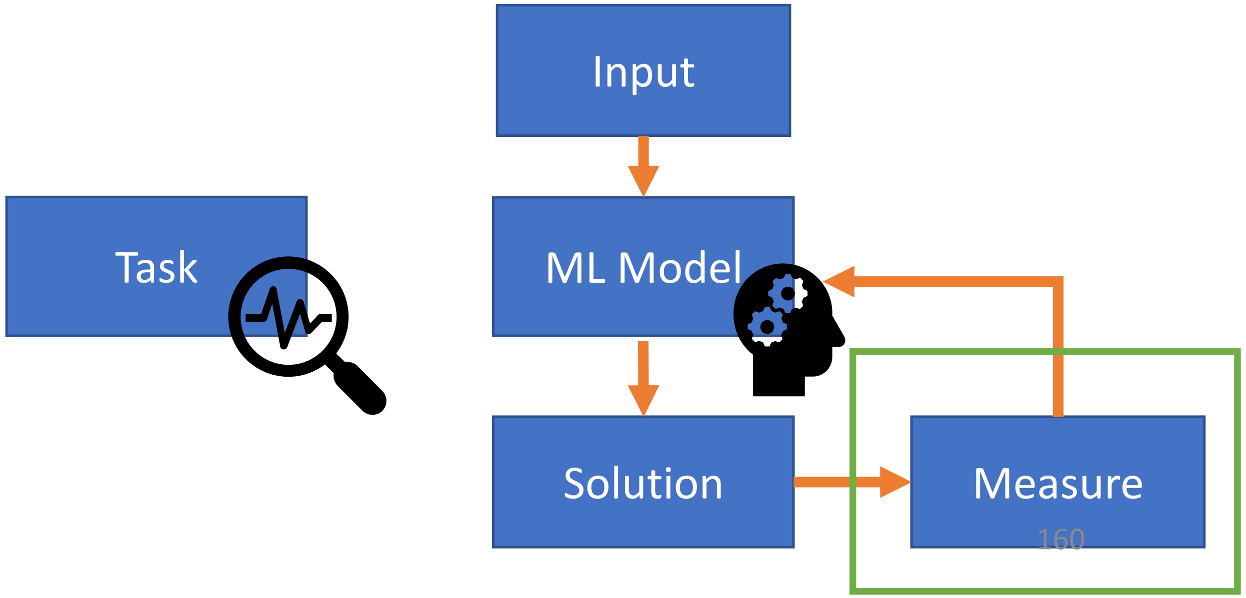

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Caution!

- Differentiate between performance measure:

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  - During learning phase (training)
    -> to improve ML model

Caution!

- Differentiate between performance measure:
  - During learning phase (training)
    -> to improve ML model
  - After learning (testing)
    -> to estimate how good your model is on unseen data

Data partitioning

- Split your data into

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  - Training data
    -> use this data to improve model during learning phase

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  - Validation data
    -> **do not** use this data during learning!
    -> use it to measure model performance on unseen data
    -> use measurement for hyperparamter tuning!

Data partitioning

- Split your data into
  - Training data
    -> use this data to improve model during learning phase
  - Validation data
    -> **do not** use this data during learning!
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  - Testing data
    -> **do not** use this data during learning!
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    -> **do not** use measurement for hyperparamter tuning!

Summary

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Outlook – Biologically inspired

- McCulloch-Pitts Cell [Tutorial]
- Perceptron [Lecture + Tutorial]
- AdaLine [Lecture + Tutorial]
- Multilayer-Perceptron (MLP) [Lecture + Tutorial]
- Convolutional Neural Networks (CNN) [Tutorial]
- Radial Basis Function-Networks (RBF-Network) [Lecture + Tutorial]

Outlook – Non-Biologically inspired

- Naive Bayes Classifier [Tutorial]
- K-Means Clustering [Lecture]
- Support Vector Machines (SVM) [Lecture + Tutorial]

Further interesting ML algorithms

- Neural Gas
- Self Organizing Maps (SOMs)
- Random Forest
- AdaBoost
- Deep Learning in general
  (we only shortly cover CNNs)

Relation to AI