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22-24 oktober 2019

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# 4 machine learning questions Azure can answer

Dr. Nico Jacobs
@SQLWaldorf

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*automatic*

*"Making predictions is hard, especially about the future"*

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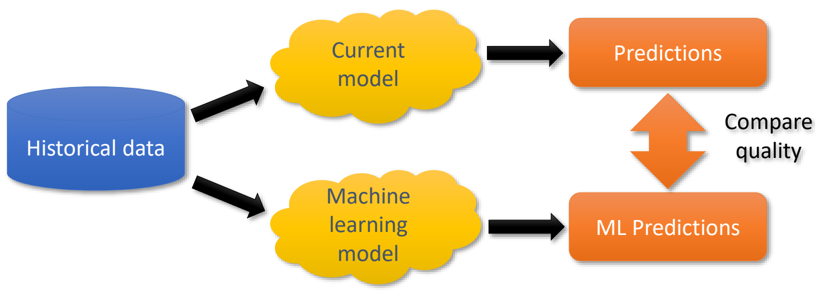
# Machine learning models

- Machine learning algorithms build models from historical data
- We compare the performance of a machine learning model against the currently used model

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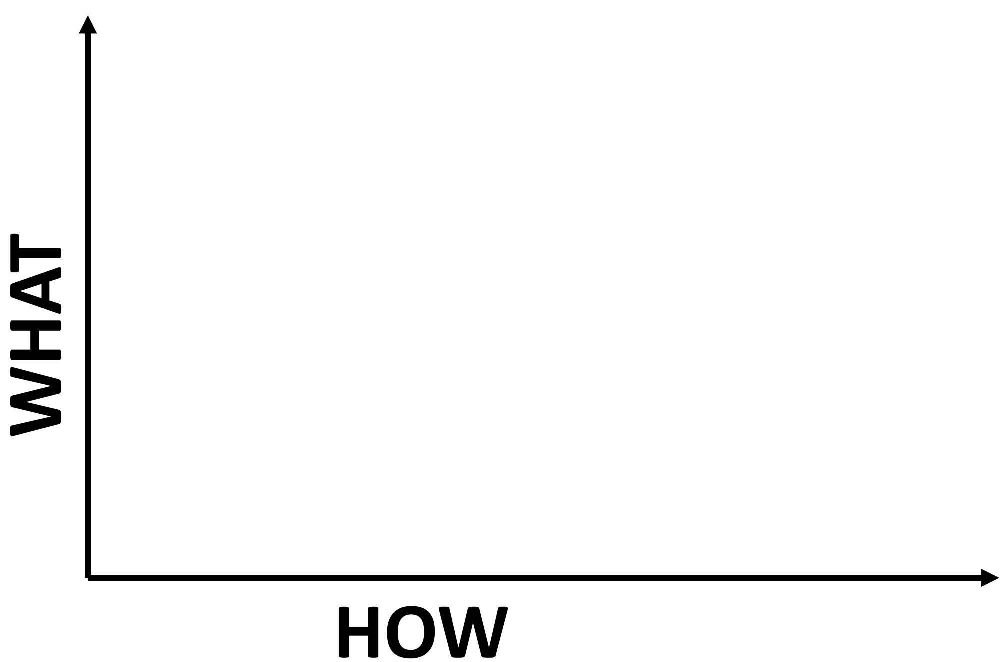


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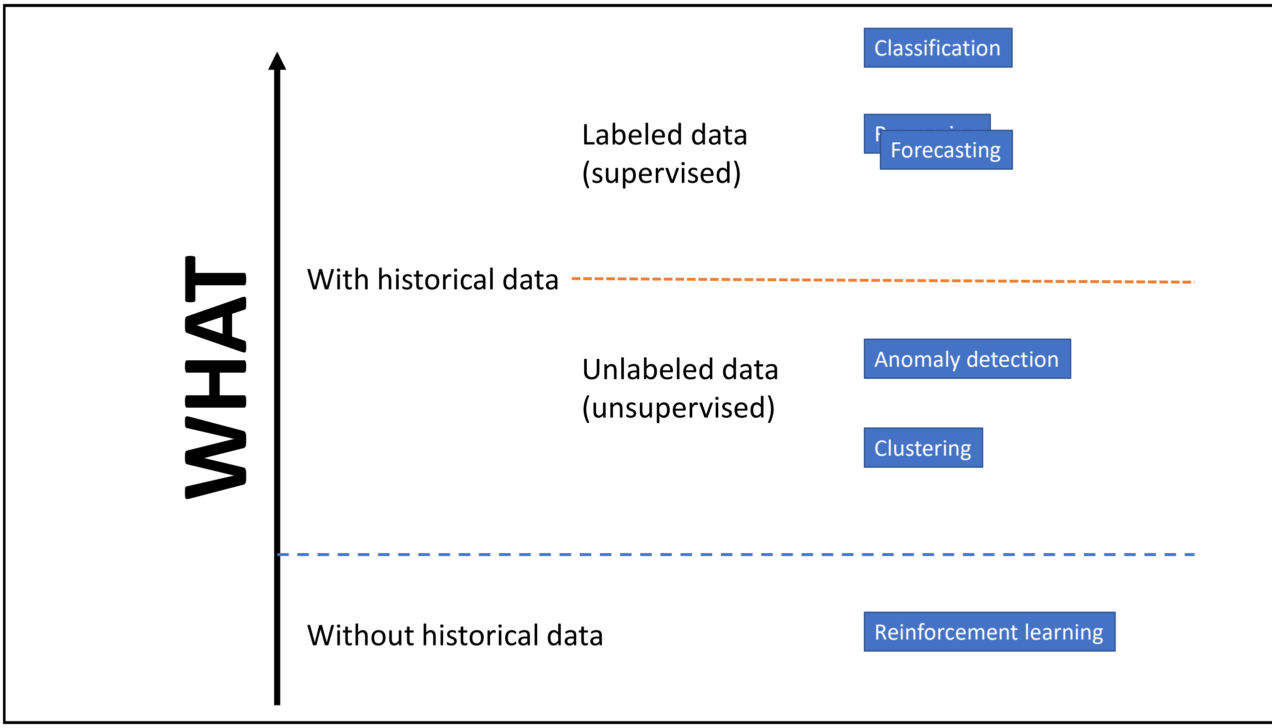


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# Learning functions

- In machine learning a function is generated which maps n input parameters on a result:

$$f(i_1, i_2, \ldots, i_n) \rightarrow result$$

- f is the model to be learned
- The inputs I are called features
- The result is called the label
- If f is created based on labeled data it is called supervised learning, else it is called unsupervised learning

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# Learning functions

- In machine learning a function is generated which maps n input parameters on a result:

$$f(i_1, i_2, \ldots, i_n) \rightarrow result$$

- In supervised learning if the result is a class this is called classification
- In supervised learning is the result is a continuous value this is called regression
  - Unless the inputs form a time series, then it's called forecasting

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# Classification: Which group, which class?

- Will a customer churn or not?
  - f(age, gender, totalSpending) →willChurn
- Will this machine fail in the next week or not?
- Should we advertise computers, bikes or clothing to this customer?

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# Classification: Which group, which class?

- Classification predicts a discrete value
  - A prediction is right or wrong
- Most techniques distinguish between two classes
- Some techniques will combine multiple two-class classifiers to obtain a multi-class classifier
- Regression problems can be discretized into a classification problem

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# Regression: How many, how much

- What is the expected cost of a specific house X
  - f(distanceShop, distanceHighway, nrBedrooms, nrBathrooms) →price
- What is the predicted cost of car accidents caused by car insurance customer X?
- How much should we pay employee X?

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# Regression

- Type of supervised learning
- Some classification problems can be converted into regression problems:
  - High versus low income: classification
  - Predict income: regression
- More difficult to measure quality
  - Answers will always be wrong
  - But we can measure how near they are to the correct answer
  - Different quality criteria
    - No accuracy or precision, but mean absolute error etc.

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# Forecasting

- Forecasting is a special case of regression
  - f(result3DaysAgo, result2DaysAgo, result1DayAgo) →resultToday
- The training data is a time series
  - A value measured at different points in time
- Based upon a base level, a trend and seasonality one predicts the continuation of the time series
- Typical examples:
  - Predicting future stock market value
  - Predicting future demand for specific product

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## Clustering: which items belong together?

- Find groups of similar customers
  - f(age, gender, totalSpending) → clusterN
- Find groups of similar messages on social media



## Clustering

- Unsupervised learning: training data doesn’t specify the clusters
- Since the training data is not labeled there is no way to know if the result is right or wrong
- But we can measure e.g. how compact the clusters are

# Anomaly detection: what doesn't fit?

- Which credit card transactions are fraudulent?

- Occurs in supervised as well as unsupervised settings
- Can often be seen as special case of classification or regression

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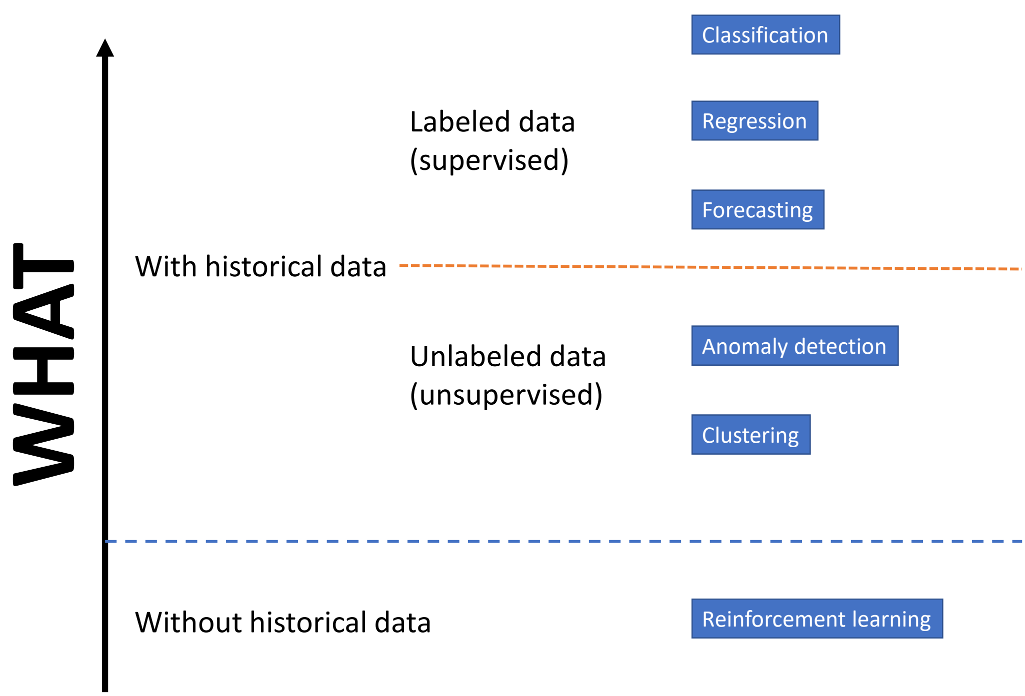


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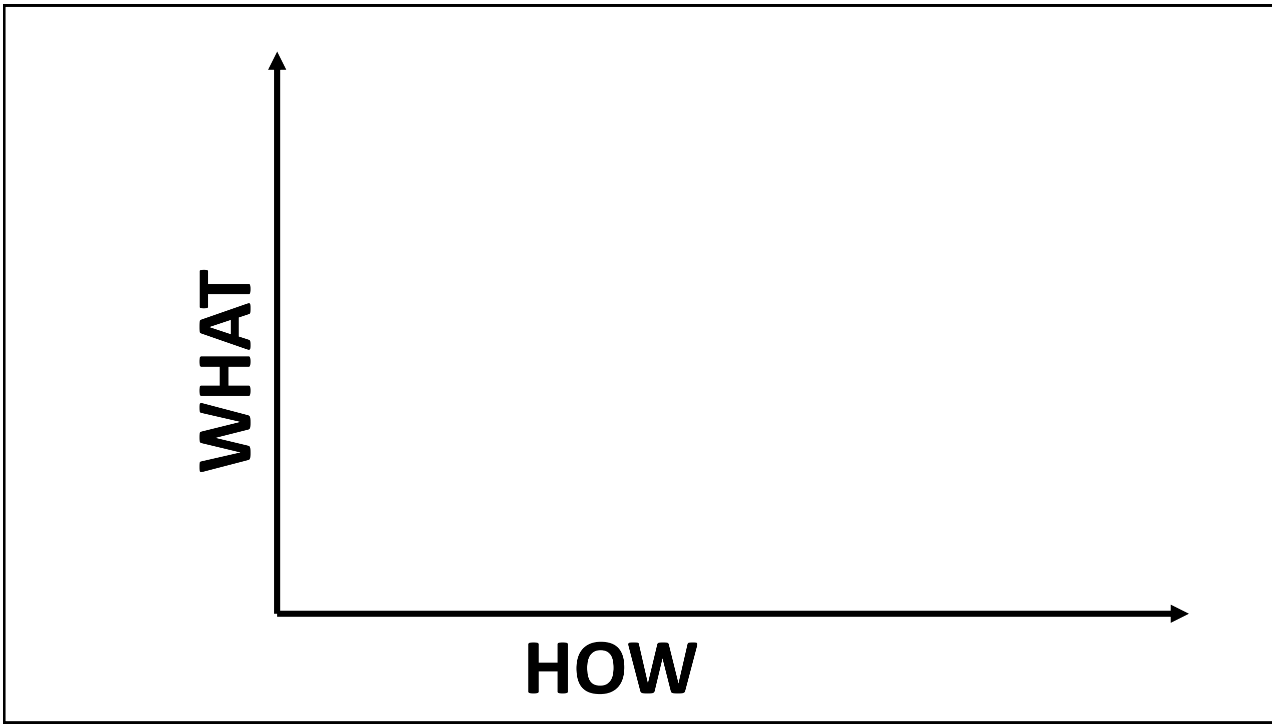
WHAT
HOW

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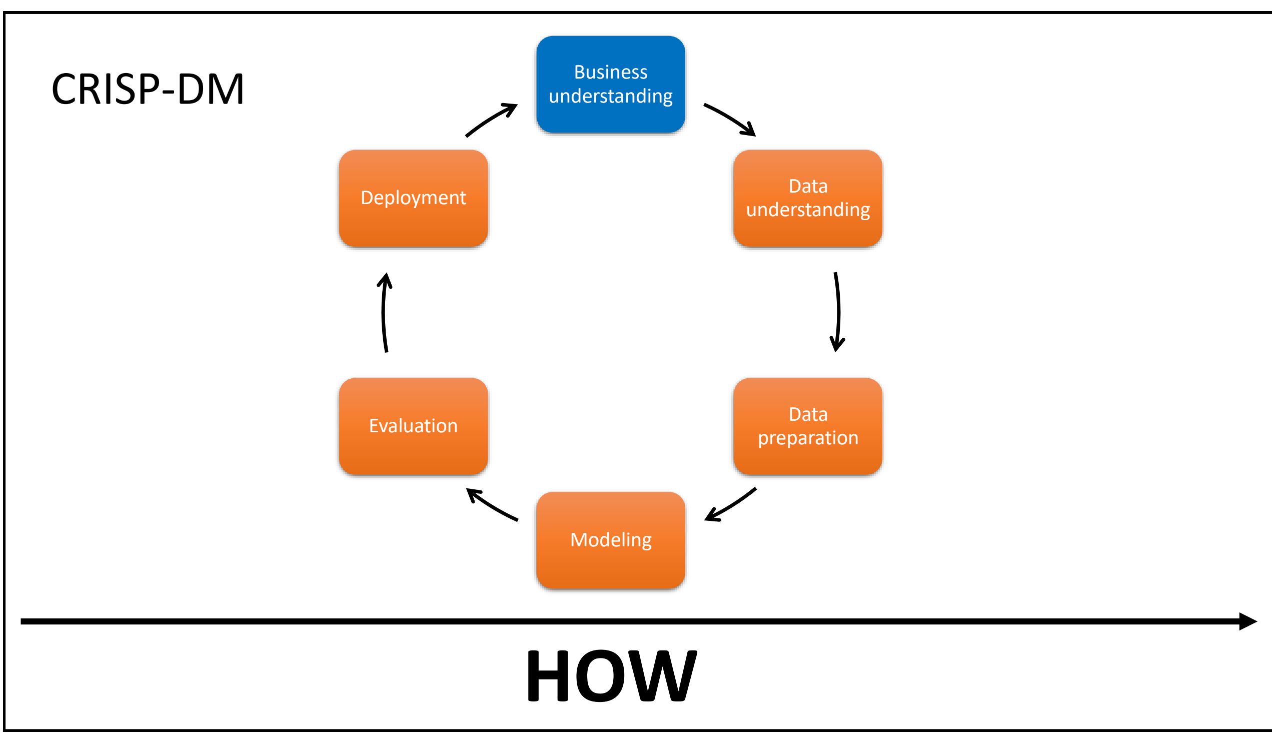
CRISP-DM
Business understanding
Data understanding
Data preparation
Modeling
Evaluation
Deployment
HOW

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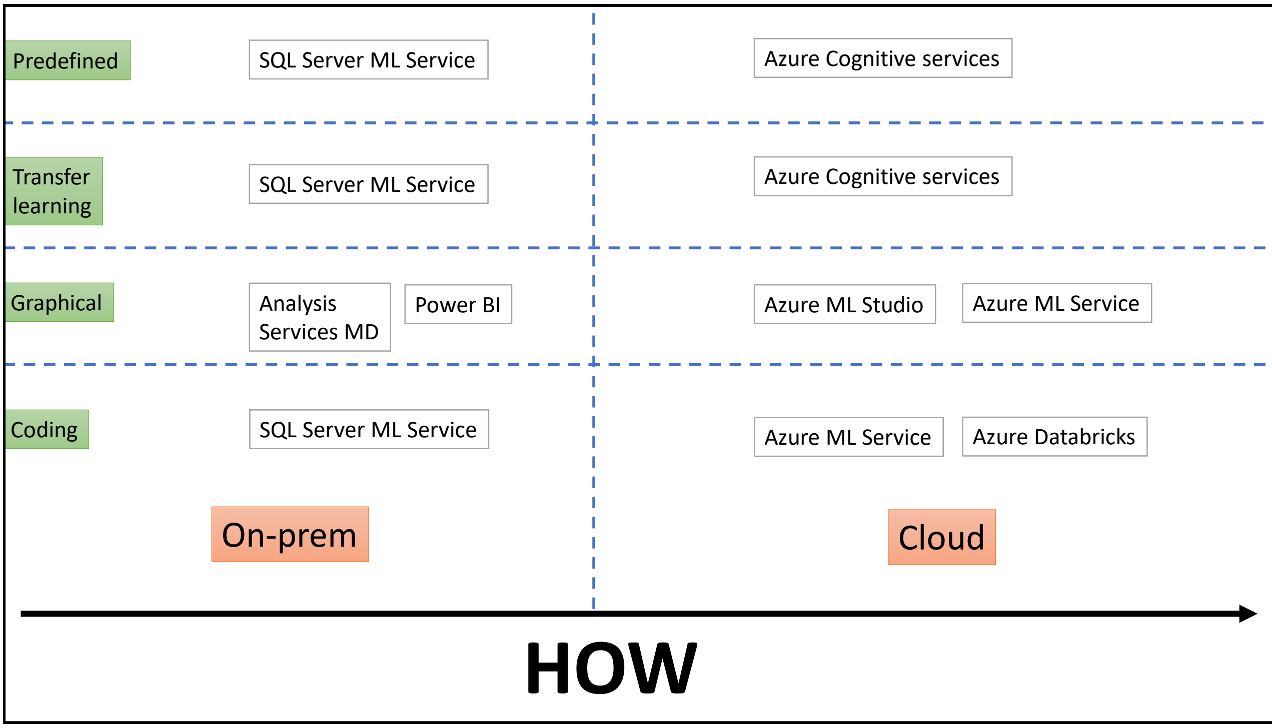
Predefined
SQL Server ML Service
Azure Cognitive services
Transfer learning
SQL Server ML Service
Azure Cognitive services
Graphical
Analysis Services MD
Power BI
Azure ML Studio
Azure ML Service
Coding
SQL Server ML Service
Azure ML Service
Azure Databricks
On-prem
Cloud
HOW

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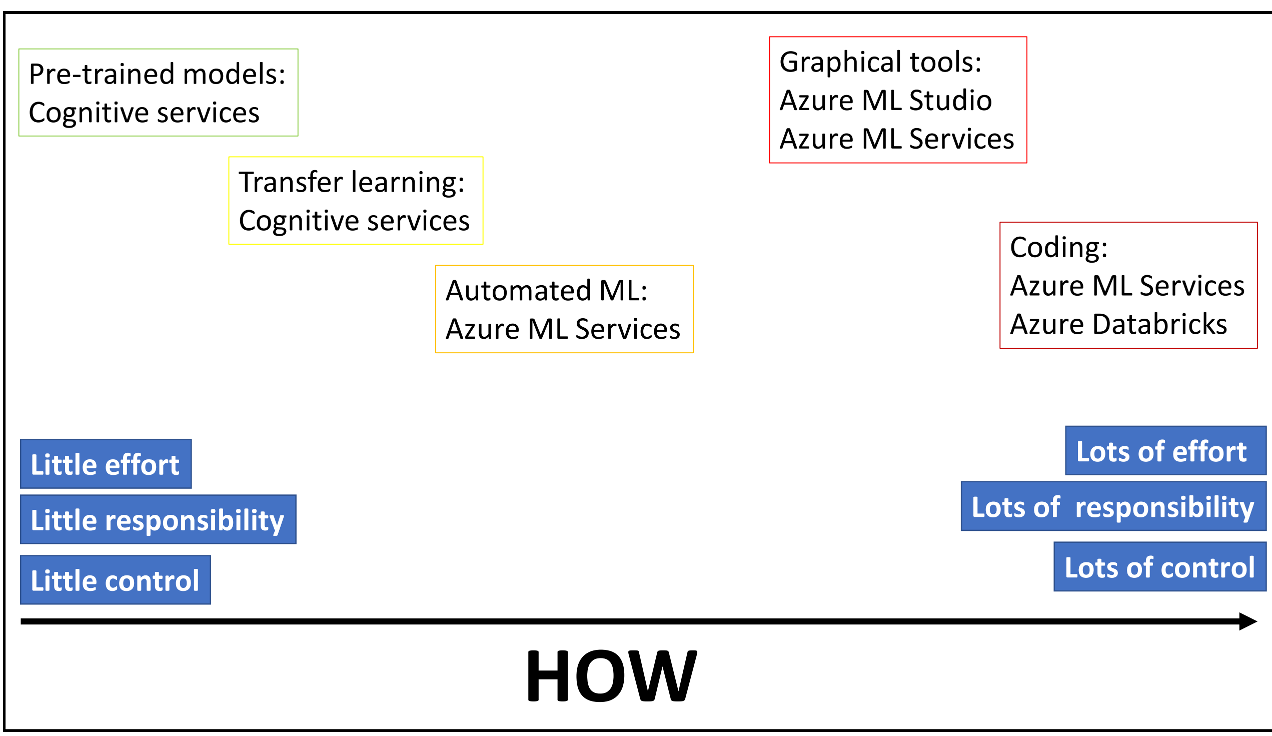
Pre-trained models:
Cognitive services
Graphical tools:
Azure ML Studio
Azure ML Services
Transfer learning:
Cognitive services
Coding:
Azure ML Services
Azure Databricks
Automated ML:
Azure ML Services
Little effort
Little responsibility
Little control
Lots of effort
Lots of  responsibility
Lots of control
HOW

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```
EXECUTE sp_execute_external_script
  @language = N'R'
  , @script = N'
    iris.sub <- c(sample(1:50, 25), sample(51:100, 25), sample(101:150, 25))
    iris.dtree <- rxDTree(Species ~ Sepal.Length + Sepal.Width + Petal.Length + Petal.Width, data=iris[iris.sub,])
    model <- rxSerializeModel(iris.dtree, realtimeScoringOnly = TRUE)    '
  , @params = N'@model varbinary(max) OUTPUT'
  , @model = @model OUTPUT
  INSERT [dbo].[ml_models]([model_name], [model_version], [native_model_object])
  VALUES('iris.dtree','v1', @model) ;
```

```
DECLARE @model varbinary(max) = (
  SELECT native_model_object
  FROM ml_models
  WHERE model_name = 'iris.dtree'
  AND model_version = 'v1');
SELECT flower.*, prediction.*
  FROM PREDICT(MODEL = @model, DATA = dbo.iris_rx_data as flower)
  WITH(setosa_Pred float, versicolor_Pred float, virginica_Pred float) as prediction
  ORDER BY [Sepal.Width]
```

Results | Messages

| Sepal.Length | Sepal.Width | Petal.Length | Petal.Width | Species | setosa_Pred | versicolor_Pred | virginica_Pred |
|---|---|---|---|---|---|---|---|
| 5 | 2 | 3.5 | 1 | versicolor | 0 | 1 | 0 |
| 6 | 2.2 | 4 | 1 | versicolor | 0 | 1 | 0 |
| 6.2 | 2.2 | 4.5 | 1.5 | versicolor | 0 | 1 | 0 |
| 6 | 2.2 | 5 | 1.5 | virginica | 0 | 0.0384615384615385 | 0.961538461538462 |

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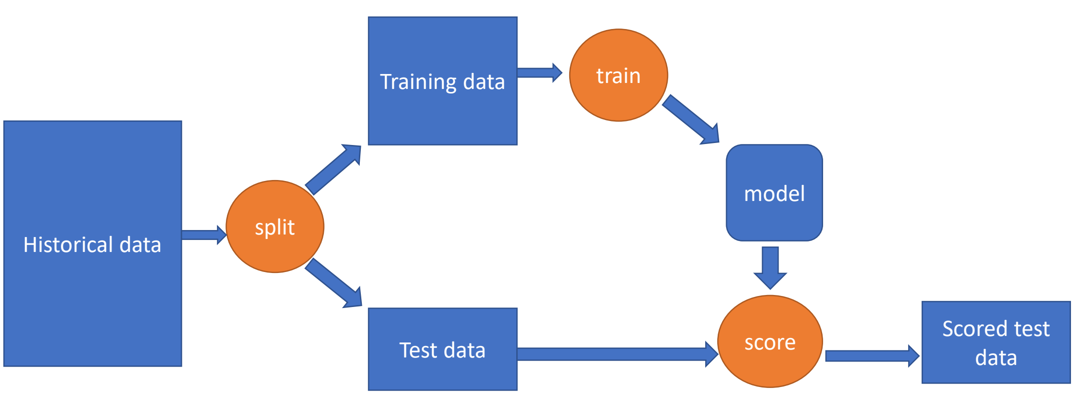
# Training a model

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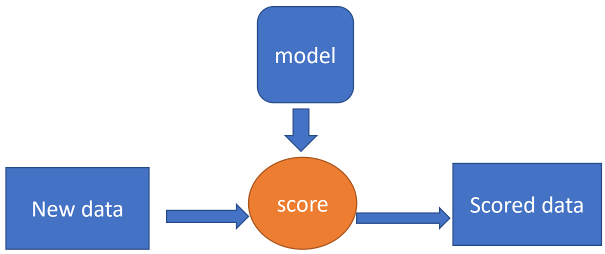
# Using a model

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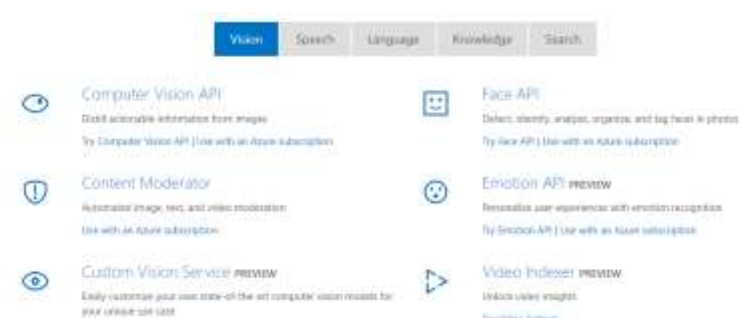
# Cognitive Services

- Cognitive services provides web services hosted in Microsoft Azure to convert text, sound, photos, …into an easier to analyze format
  - Usually json documents are returned

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# Two types of services

| Pre-trained | Transfer learning |
|---|---|
| • We just provide the input and get back a result | • Microsoft provides a framework within which we can further train or customize the service |

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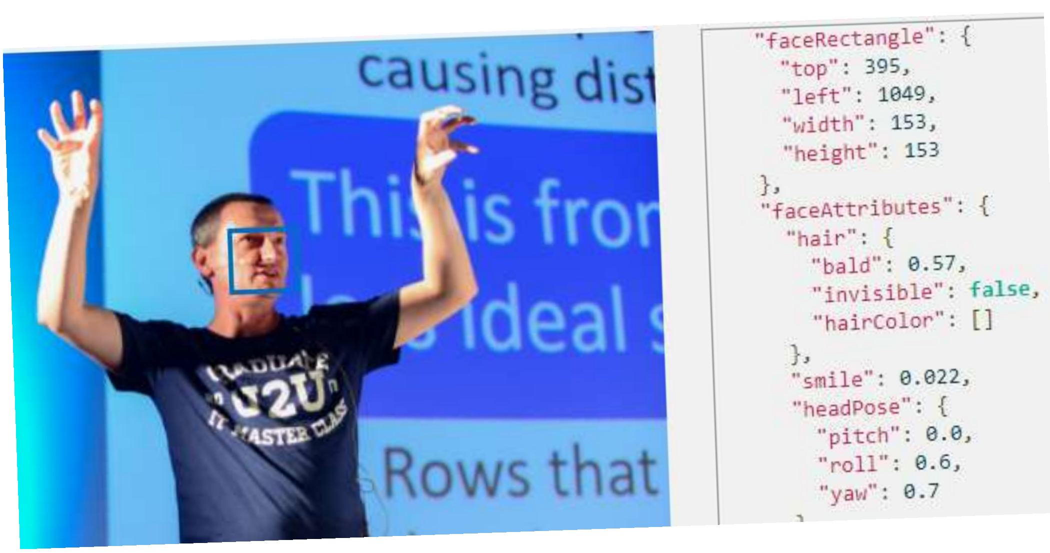


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# Ink recognizer


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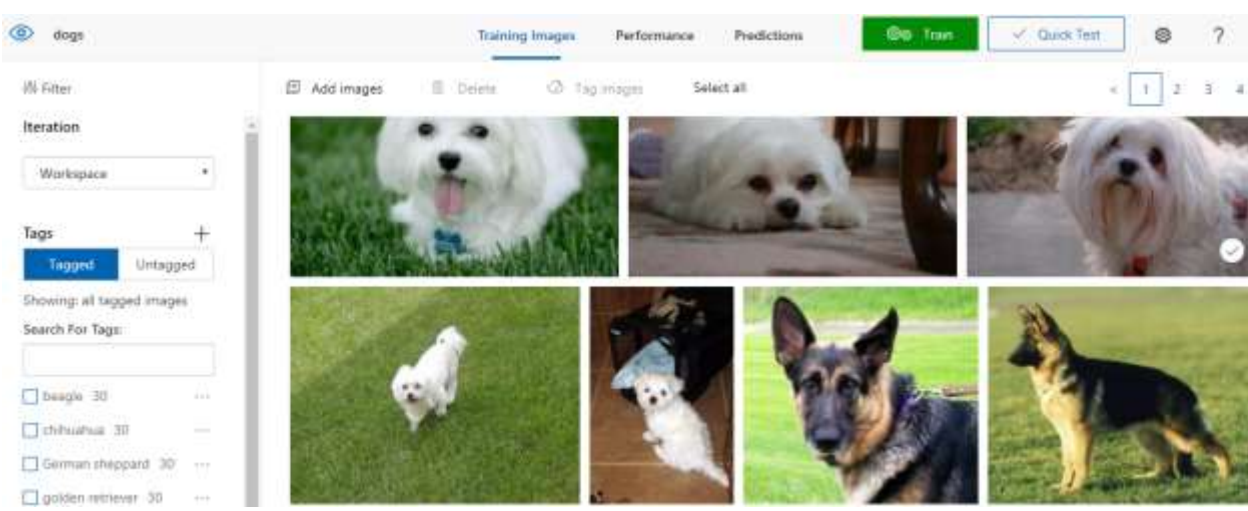
# Transfer learning: custom vision

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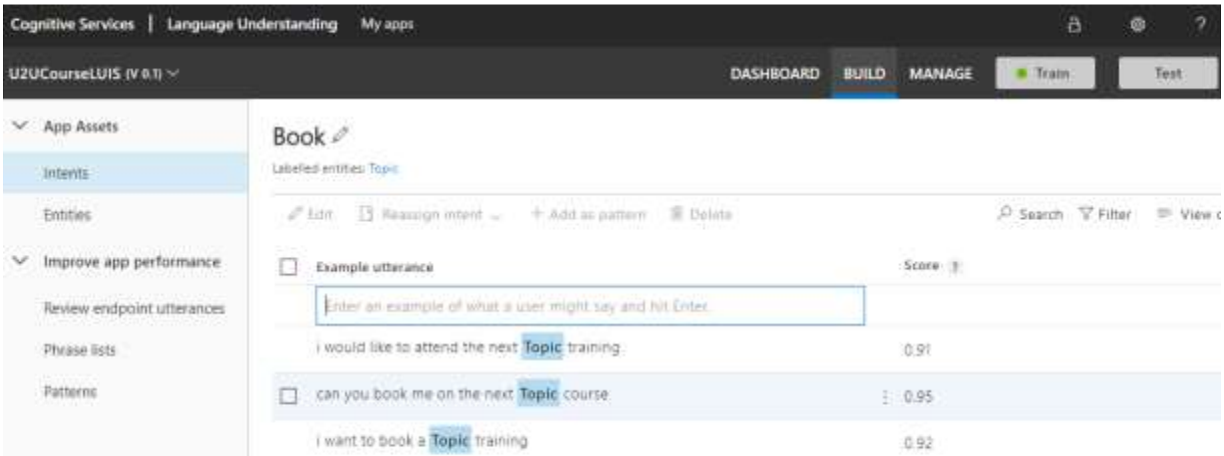
# Transfer learning: LUIS

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# Azure Machine Learning Studio

- Azure ML Studio starts from https://studio.azureml.net
- It comes with a graphical interface in which users develop a data mining workflow
- The models resulting from these flows can then be converted into an Azure web service for scoring new data

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## Demo: ML Studio

Titanic data set

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## 3 ways to use Azure ML Services

| Do It Yourself | Graphical approach | Automated ML |
| --- | --- | --- |
| • Ideal if you want to write or reuse Python code<br>  • Scikit-learn, Tensorflow, PyTorch, Keras,… | • Like Azure Machine Learning Studio, where a model is created with a drag-and-drop interface | • Automated ML uses a trial-and-error approach to build a reasonable model |

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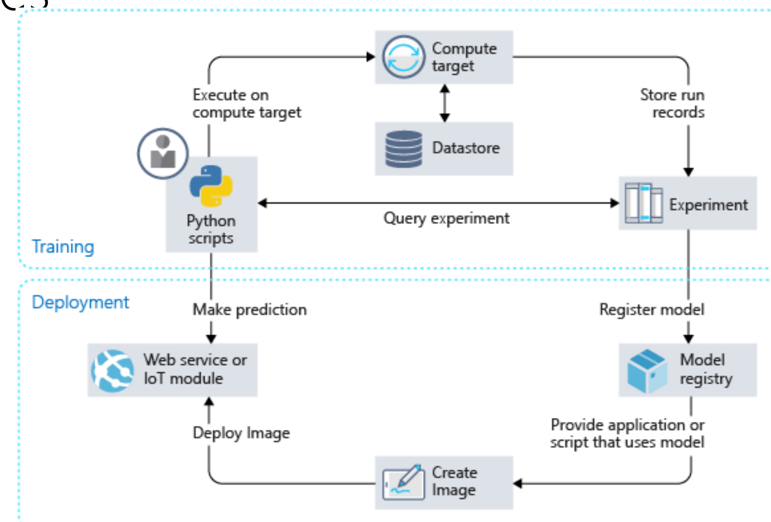
# Architecture Azure Machine Learning Services




(https://docs.microsoft.com/en-us/azure/machine-learning/service/concept-azure-machine-learning-architecture)

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# Demo: Azure ML Services

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# Azure Databricks

- Designed by Spark developers
- Collaborative platform
- 10 times faster than vanilla spark
- Easy setup and administration
- Native integration with Azure services
  - Power BI
  - SQL Data Warehouse
  - Cosmos Db
  - Blob Storage
- Azure Active Directory integration
- Enterprise grade SLA

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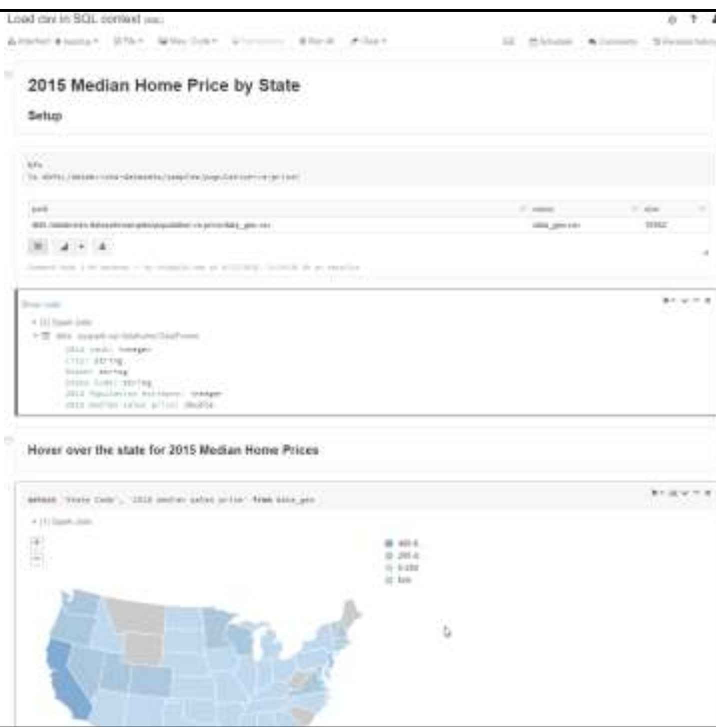


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# Thank you!

Please take the opportunity to evaluate this session in the app

Download slidedeck from https://github.com/SqlWaldorf/talks/

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