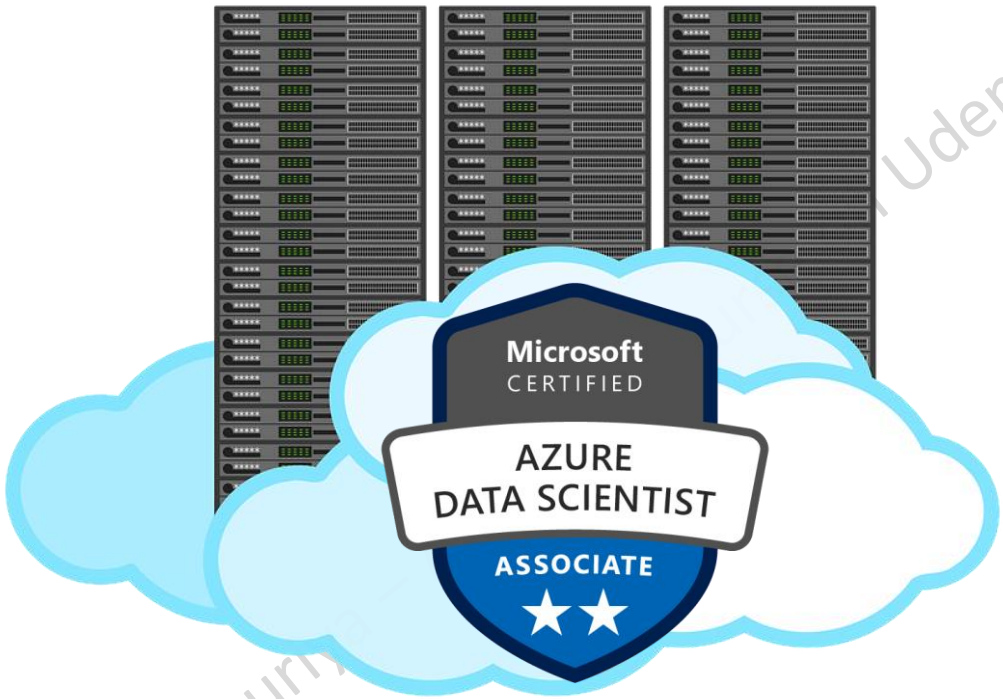
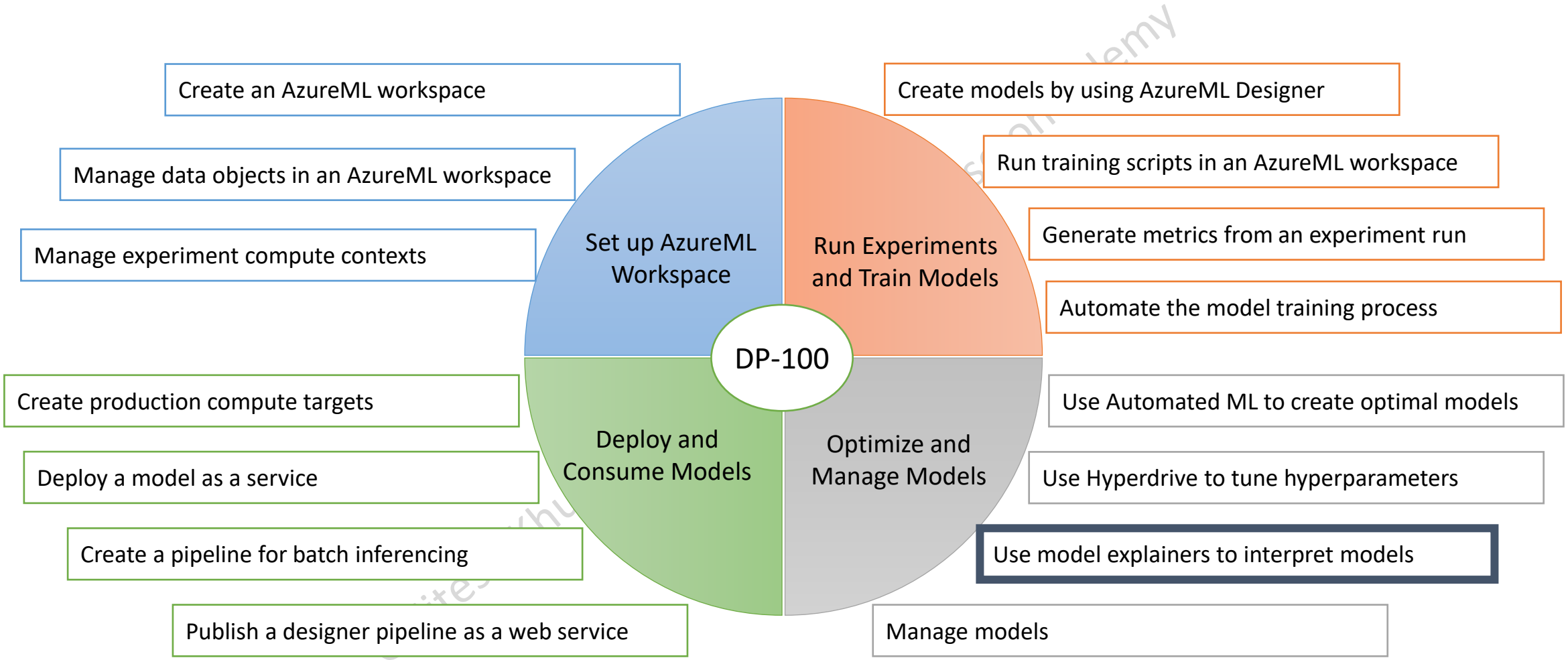
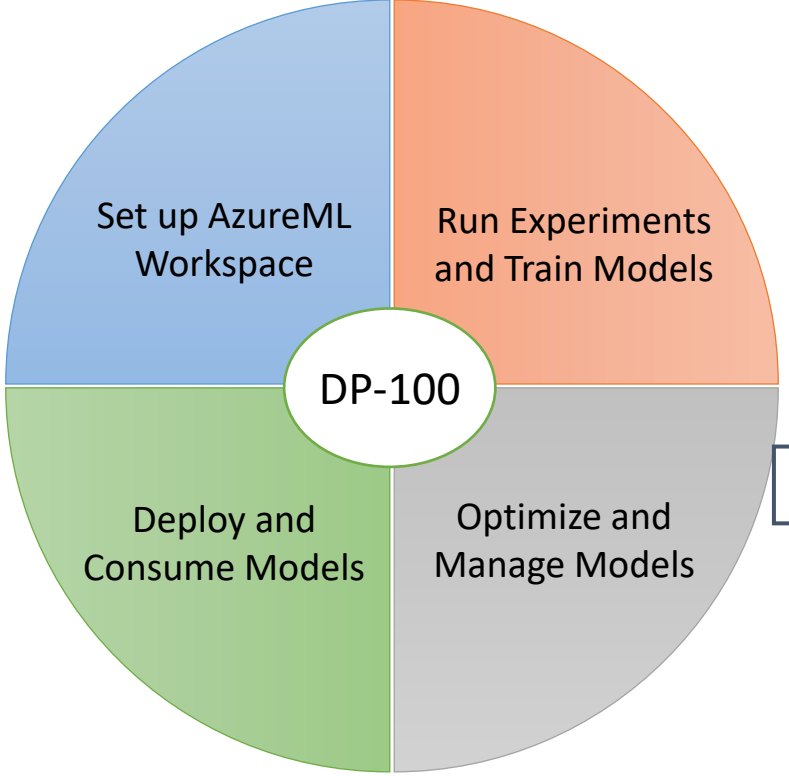


Azure Machine Learning

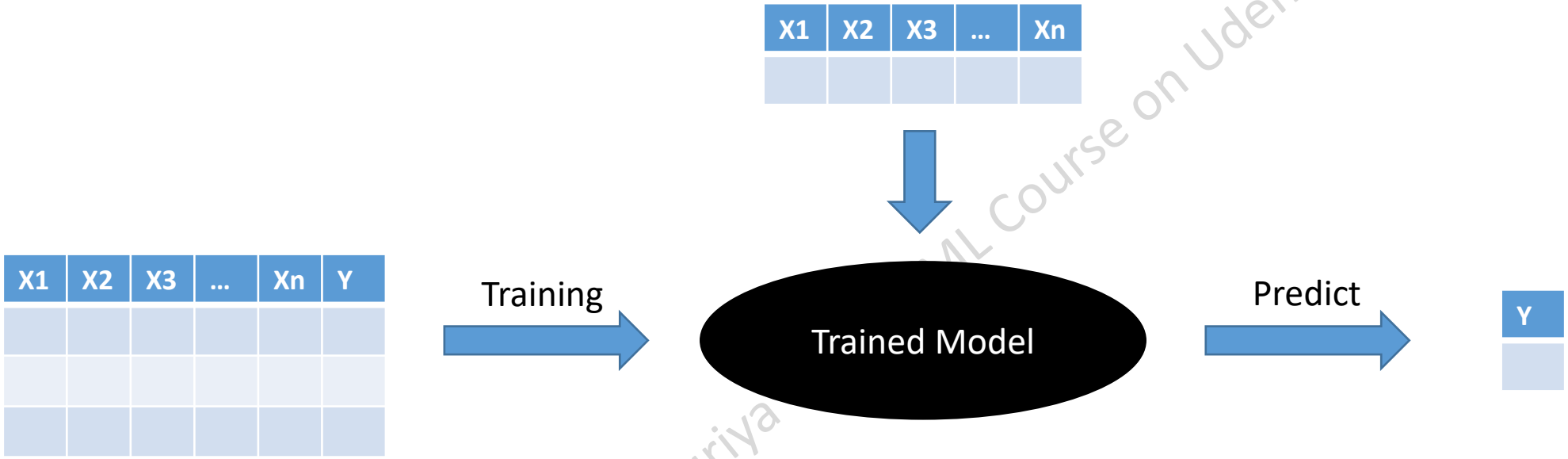




Use model explainers to interpret models

- Select a model interpreter
- Generate feature importance data

What do we mean by Model Interpretation?



What was the impact of these features on prediction?

Which Features are important?

Role played by every feature in total as well as individual predictions?

Role played by every feature in Production Predictions?

`sklearn.feature_selection`: Feature Selection

The `sklearn.feature_selection` module implements feature selection algorithms. It currently includes univariate filter selection methods and the recursive feature elimination algorithm.

User guide: See the Feature selection section for further details.

`feature_selection.GenericUnivariateSelect`([...])	Univariate feature selector with configurable strategy.
`feature_selection.SelectPercentile`([...])	Select features according to a percentile of the highest scores.
`feature_selection.SelectKBest`([score_func, k])	Select features according to the k highest scores.
`feature_selection.SelectFpr`([score_func, alpha])	Filter: Select the pvalues below alpha based on a FPR test.
`feature_selection.SelectFdr`([score_func, alpha])	Filter: Select the p-values for an estimated false discovery rate
`feature_selection.SelectFromModel`(estimator, *)	Meta-transformer for selecting features based on importance weights.
`feature_selection.SelectFwe`([score_func, alpha])	Filter: Select the p-values corresponding to Family-wise error rate
`feature_selection.SequentialFeatureSelector`(...)	Transformer that performs Sequential Feature Selection.
`feature_selection.RFE`(estimator, *[, ...])	Feature ranking with recursive feature elimination.
`feature_selection.RFECV`(estimator, *[, ...])	Feature ranking with recursive feature elimination and cross-validated selection of the best number of features.
`feature_selection.VarianceThreshold`([threshold])	Feature selector that removes all low-variance features.

`feature_selection.chi2`(X, y)	Compute chi-squared stats between each non-negative feature and class.
`feature_selection.f_classif`(X, y)	Compute the ANOVA F-value for the provided sample.
`feature_selection.f_regression`(X, y, *[, center])	Univariate linear regression tests.
`feature_selection.mutual_info_classif`(X, y, *)	Estimate mutual information for a discrete target variable.
`feature_selection.mutual_info_regression`(X, y, *)	Estimate mutual information for a continuous target variable.

Why Interpretability is Important?

Data Scientists

- Ability to explain model findings to others
- Ability to debug the model and identify issues
- Improve the model

Business Decision Makers

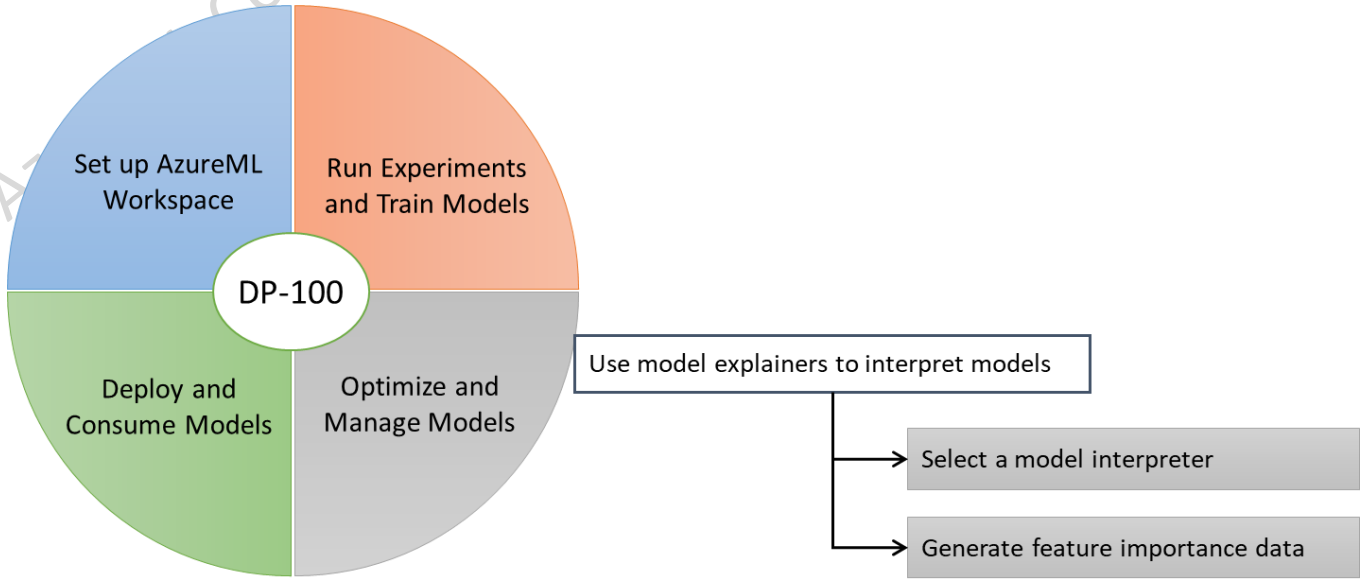
- Provide transparency to end users
- Understand and justify the business case for investment
- Identify more use cases based on business scenarios

Key Approving Authorities

- Understand the risks by model implementations
- Understand the impact of decisions on humans
- Understand potential legal issues

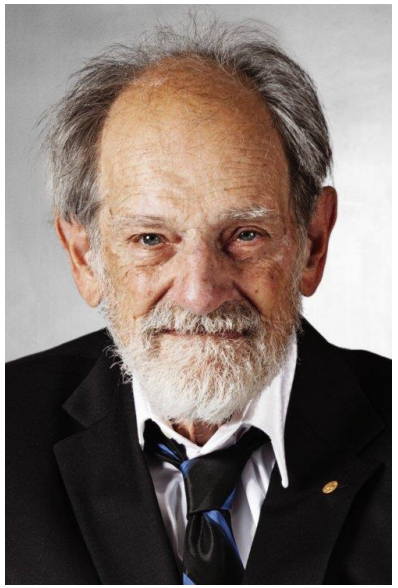
What will we learn?

- **azureml-interpret** using interpret-community
- Different interpretability techniques for different type of algorithms
- Local Vs Global Explanations
- Shapley Values for feature importance



Shapley Value

- Introduced in 1951 by Lloyd Shapley and won Noble Prize for it in 2012
- Solution concept in the cooperative game theory
- Creates a unique distribution among the players who generate some gain or cost



Lloyd Shapley

Shapley Value

Alen

Bob

Cindy

$ 4

$ 6

$ 20

Shapley Value

Alen

Bob

Cindy

$ 20

Shapley Value

$ 20

Alen – 1

$ 6

Bob – 2

$ 4

Cindy – 3

{ 0 } = 0

{ 1 } = 20

{ 2 } = 6

{ 3 } = 4

{ 1, 2 } = 20

{ 1, 3 } = 20

{ 2, 3} = 6

{ 1, 2, 3} = 20

https://en.wikipedia.org/wiki/Shapley_value

$$\varphi_i(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(N - |S| - 1)!}{N!} (v(S \cup \{i\}) - v(S))$$

http://shapleyvalue.com/

Shapley Value

$ 20

Alen – 1

$ 6

Bob – 2

$ 4

Cindy – 3

{ 0 } = 0

{ 1 } = 20

{ 2 } = 6

{ 3 } = 4

{ 1, 2 } = 20

{ 1, 3 } = 20

{ 2, 3} = 6

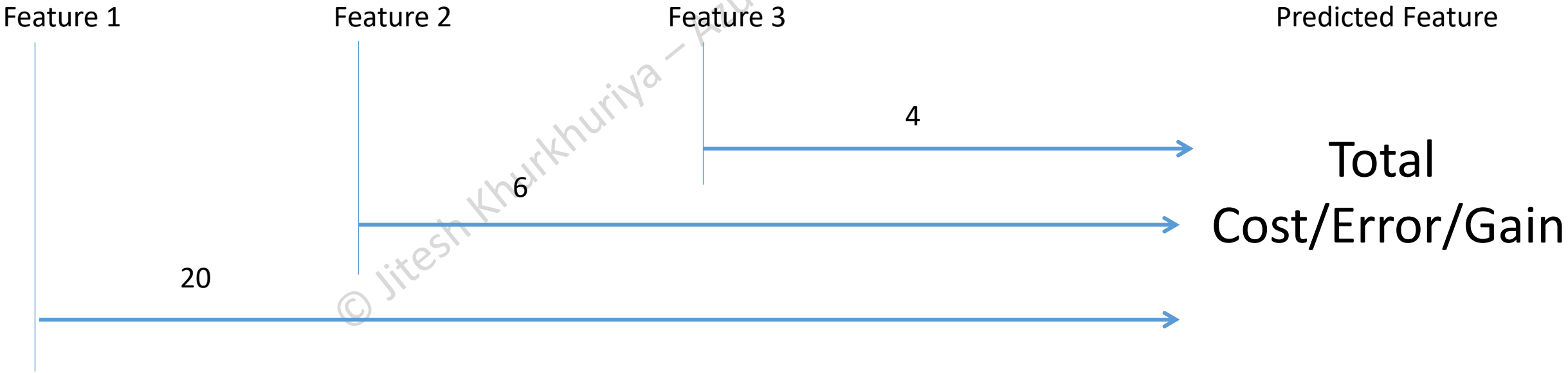
{ 1, 2, 3} = 20

The Shapley value of Alen is : 16.33

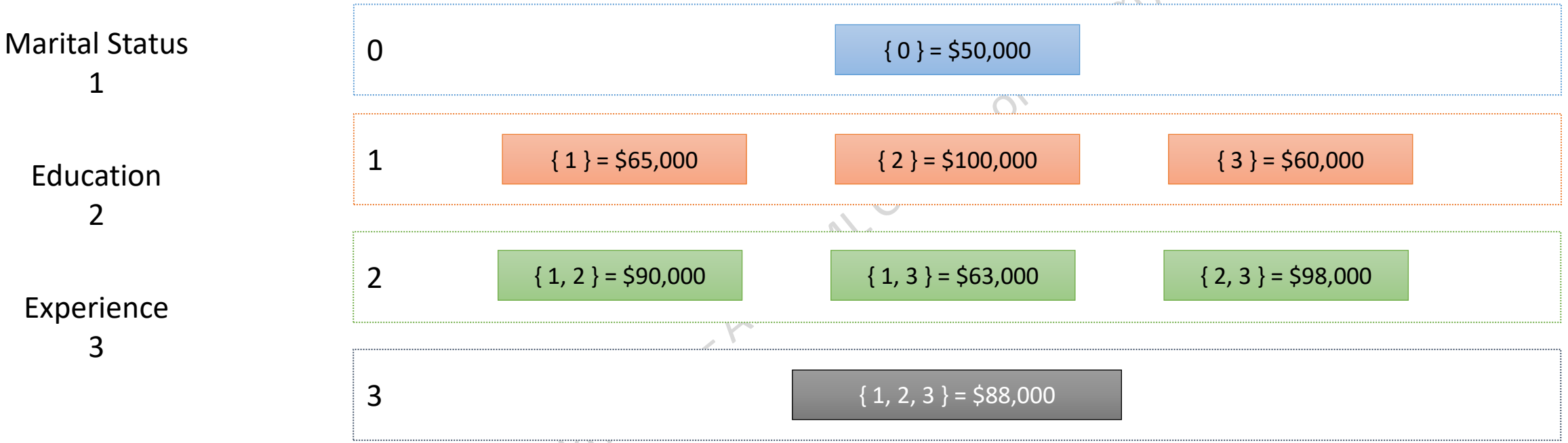
The Shapley value of Bob is : 2.33

The Shapley value of Cindy is : 1.33

Shapley Value



Adult Income Prediction



Feature Importance
Local

The Shapley value of Marital Status : $ 500

The Shapley value of Education : $ 35,500

The Shapley value of Experience : $ 2,000

$38,000 = $88,000 – $50,000

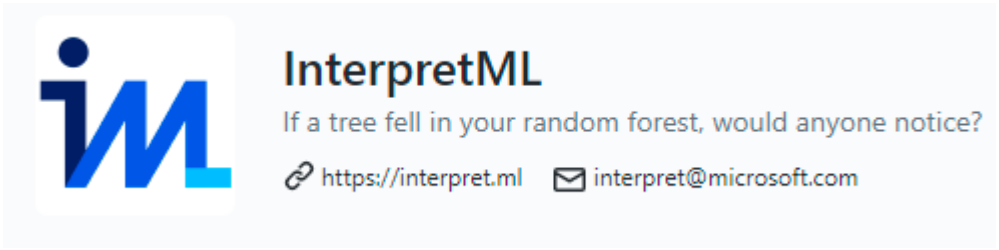
Local Vs Global Interpretability

Global	Local

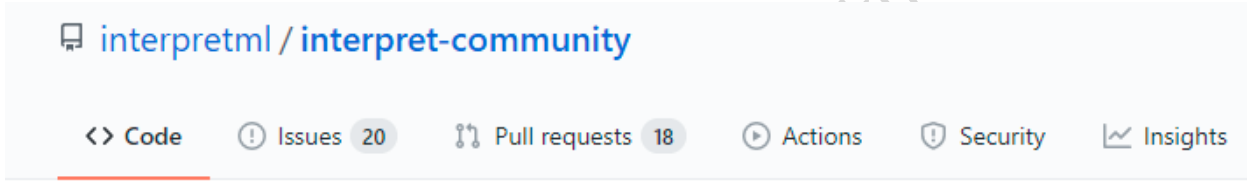
• Top important features for the entire prediction set
 	
• Takes into account entire training or test dataset
 	
• Example – Which features are important to get this accuracy or any other primary metric?
  • Education
  • **Marital Status**
  • **Age**
  • Race
	• Top important features for an individual prediction
	
	• Takes into account just one record of independent features
	
	• Example – Which top features predicted that Bob has income higher than $50K?
	  • Education
	  • **Age**
	  • **Marital Status**
	  • Race

azureml.interpret

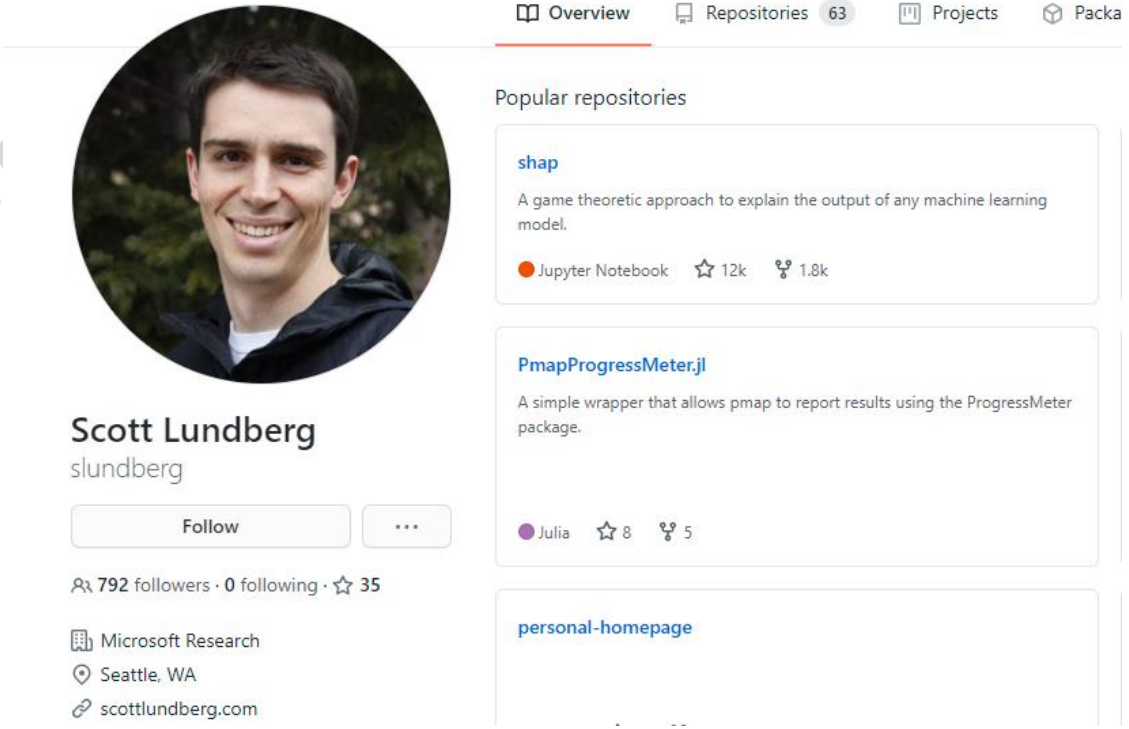
https://github.com/interpretml
https://interpret.ml/



https://github.com/interpretml/interpret-community



https://github.com/slundberg



https://github.com/slundberg/shap

azureml.interpret

Interpretability Technique	Description	Type
SHAP Tree Explainer	Focuses on Trees and Ensemble Tree algorithms such as Decision Tree, Random Forest etc.	Model Specific
SHAP Deep Explainer	Supports the explanations for the deep learning models such as Tensorflow and PyTorch	Model Specific
SHAP Linear Explainer	Supports linear models such as Linear Regression, Logistic Regression	Model Specific
SHAP Kernel Explainer	Supports every model	Model Agnostic
Mimic Explainer	Creates a surrogate model to mimic the behavior of the Black Box model.	Model Agnostic
Permutation Feature Importance Explainer	It works by randomly shuffling the dataset one feature at a time and checks how much the primary metric changed by addition or deletion of the feature. Larger the change, more important is the feature.	Model Agnostic

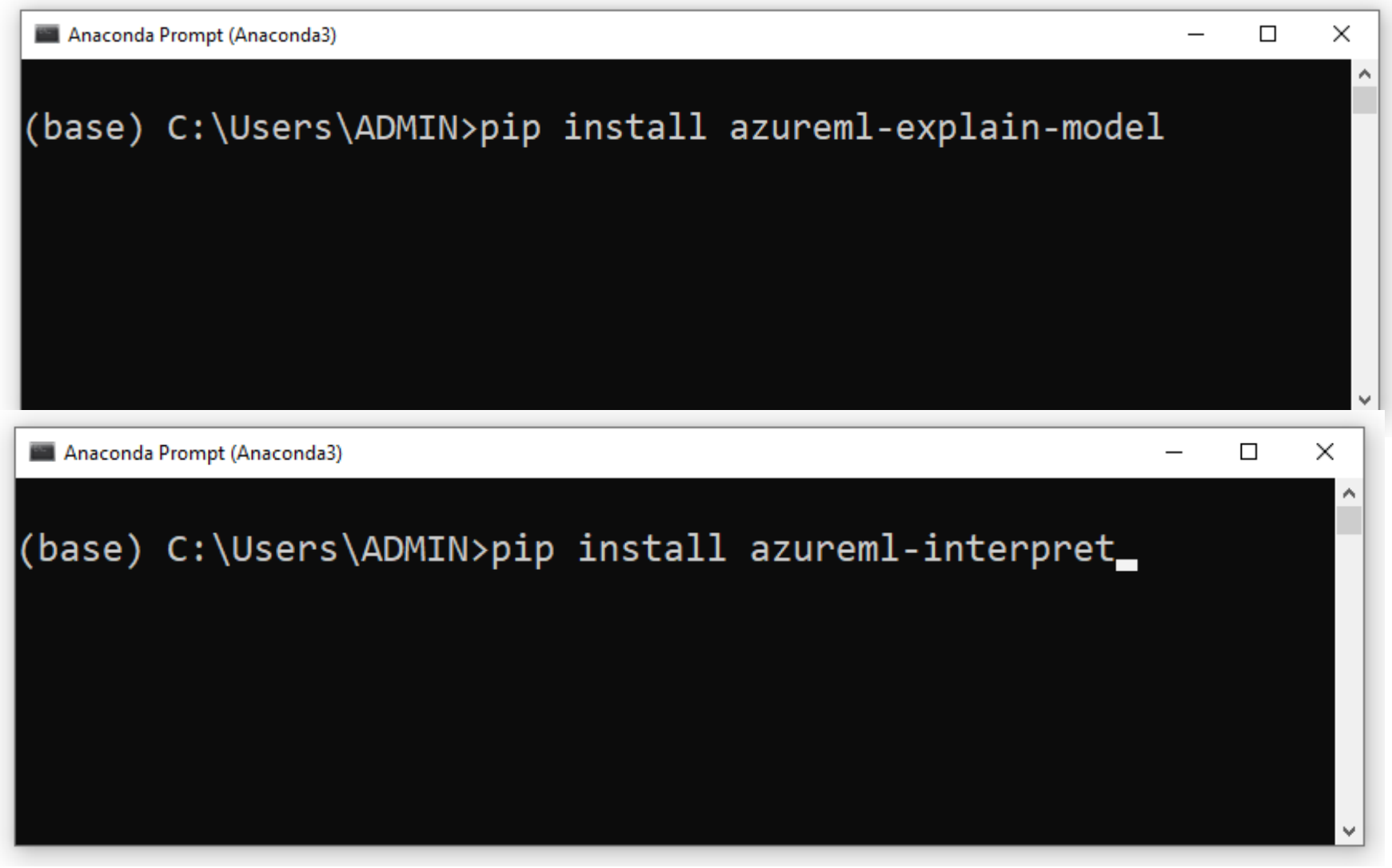
TabularExplainer

- SHAP-based explainer for tabular data
- TreeExplainer for all tree-based models
- DeepExplainer for DNN models
- LinearExplainer for linear models
- KernelExplainer for all other models

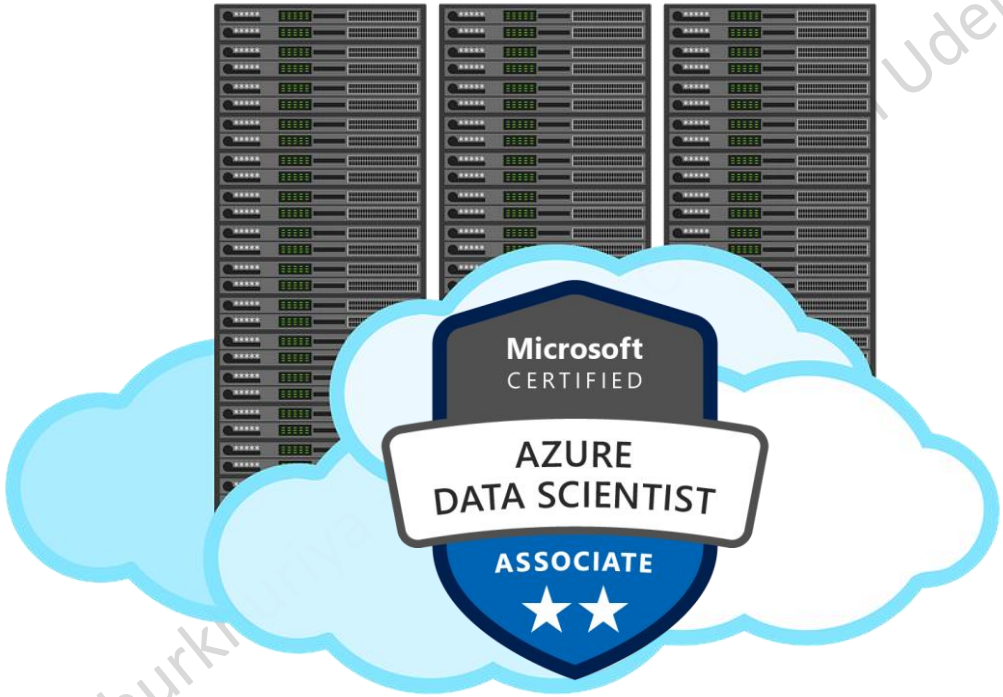
Benefits of Azureml interpret

- Explain the entire model behavior or individual predictions locally as well as in Azure
- Enable interpretability techniques for engineered features.
- Use a visualization dashboard to interact with your model explanations.
- Deploy a scoring explainer alongside your model to observe explanations during inferencing.

Mandatory Installs



Azure Machine Learning



Thank You..!!