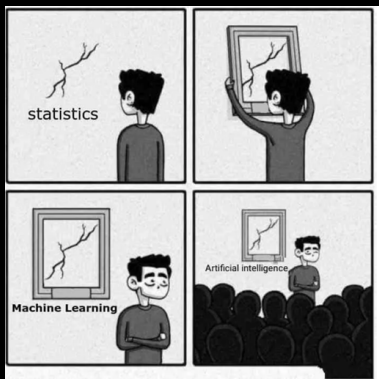


Week 03- Session 01 - Regression



Kelvin C. - PassDowns/Walkthroughs III

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Supervised Learning Overview

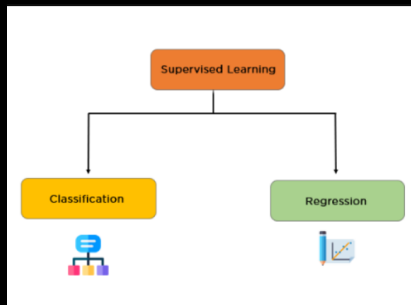


Figure: Illustration of Classification.

- ▶ **Supervised learning:** Learning a function that maps inputs to outputs based on labeled data.
- ▶ Two main types:
 - ▶ **Classification:** Predict discrete labels.
 - ▶ **Regression:** Predict continuous values.

Regression: Problem Setup



Regression on predicting house price

- ▶ Goal: Predict a continuous output y given input features x .
- ▶ Examples:
 - ▶ Predict house prices based on features like size, location.
 - ▶ Predict temperature based on time of day.

Univariate Linear Regression

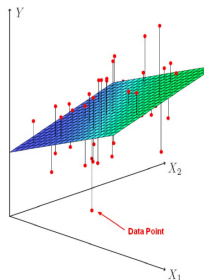
- ▶ One input feature x , output y .
- ▶ Hypothesis function:

$$h_{\theta}(x) = \theta_0 + \theta_1 x$$

- ▶ θ_0 : intercept, θ_1 : slope.

Multivariate Linear Regression

y	x_1	x_2
140	60	22
155	62	25
159	67	24
179	70	20
192	71	15
200	72	14
212	75	14
215	78	11



Regression on predicting house price

- ▶ Multiple input features $\mathbf{x} = (x_1, x_2, \dots, x_n)$.
- ▶ Hypothesis function:

$$h_{\theta}(\mathbf{x}) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n$$

- ▶ Vectorized form:

$$h_{\theta}(\mathbf{x}) = \theta^T \mathbf{x}$$

where $\mathbf{x} = [1, x_1, x_2, \dots, x_n]^T$

Cost Function

- ▶ Measures how well the hypothesis fits the data.
- ▶ Mean Squared Error (MSE) cost function:

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

- ▶ m = number of training examples.
- ▶ Goal: find θ that minimizes $J(\theta)$.

Gradient Descent Algorithm(Click for proof)

- ▶ Optimization algorithm to minimize cost function.
- ▶ Update rule for each parameter θ_j :

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

- ▶ For linear regression:

$$\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_j^{(i)}$$

- ▶ α is the learning rate.

Regression Performance Metrics

- ▶ **Mean Squared Error (MSE):**

$$\text{MSE} = \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

- ▶ **Root Mean Squared Error (RMSE):**

$$\text{RMSE} = \sqrt{\text{MSE}}$$

- ▶ **Mean Absolute Error (MAE):**

$$\text{MAE} = \frac{1}{m} \sum_{i=1}^m |h_{\theta}(x^{(i)}) - y^{(i)}|$$

- ▶ **R-squared (R^2):**

$$R^2 = 1 - \frac{\sum (y^{(i)} - h_{\theta}(x^{(i)}))^2}{\sum (y^{(i)} - \bar{y})^2}$$

where \bar{y} is the mean of $y^{(i)}$.

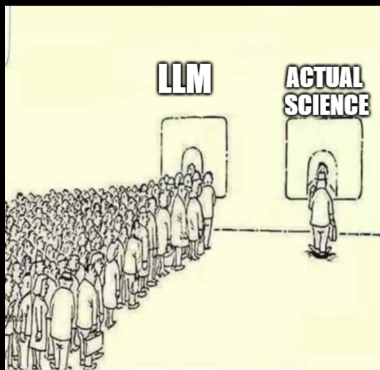
Summary

- ▶ Supervised learning: regression predicts continuous output.
- ▶ Univariate vs multivariate linear regression.
- ▶ Hypothesis function models the relationship.
- ▶ Cost function measures prediction error.
- ▶ Gradient descent optimizes parameters.
- ▶ Performance metrics evaluate regression quality.

Discrete Event Simulation (DES)



Week 03- Session 02 - Discrete Event Simulation



Kelvin C. - PassDowns/Walkthroughs III

DES-Intro

DES is a modelling technique where the operation of a system is represented as a chronological sequence of events. Each events occurs at a discrete point in time and changes the systems's state.

Characterisitcs

- ▶ Models complex, stochastic systems without oversimplifying
- ▶ Tracks entities, events and systems states over time
- ▶ Events can include arrival, departure, breakdown, repairs, etc.

Applications

- ▶ Manufacturing production (assembly lines,production line, warehouse inventory)
- ▶ Airport operation(baggage handling/routing,check-in systems)
- ▶ Logistics and supply chains (warehouse planning)
- ▶ Healthcare systems (patient flow in Accident & Emergency Department)

Discrete Event Simulation for Lead Time Forecasting

- ▶ **Context:** Manufacturing production line with queues at various stages
- ▶ **Goal:** Forecast lead times by modeling the dynamics of work-in-progress
- ▶ **What is Discrete Event Simulation (DES)?**
 - ▶ A computational method that models the operation of a system as a sequence of discrete events
 - ▶ Events correspond to changes in system state, e.g., job arrival, processing start/end, queue departure
- ▶ **Why use DES for queuing theory?**
 - ▶ Captures stochastic variability in arrivals and processing times
 - ▶ Provides detailed insights into queue lengths, queue duration, waiting times, and bottlenecks
 - ▶ Enables evaluation of different production scenarios and policies

The end of Walkthroughs.....



TBT of Data Scientist's MO.