

# Hiring with Artificial Intelligence

---

*Group 10: Noah Minard, Subash Adusumilli, Joel Chaple, Lewi Anamo*

# Driving Questions:

*“How well can AI select the best job candidate(s) from applications and interviews?”*

*“What models are the most accurate in doing so?”*



# Motivation:

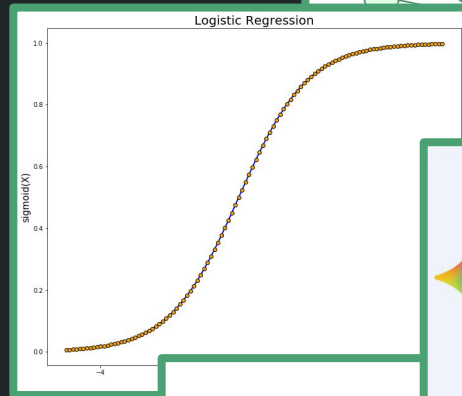
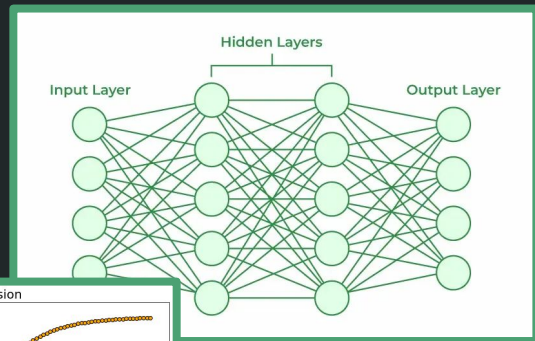
- ❖ Millions of job applications are handled every year in the U.S.
  - ❖ Candidate assessment processes are often time + resource consuming
  - ❖ AI/ML tools promise fast and consistent hiring decisions
  - ❖ Can these tools make accurate and unbiased choices in hiring?
-

# Methods:

*Clean Data   Test Models   Analyze Results*

Models evaluated include:

- ❖ Neural Network Model
- ❖ Logistic Regression Model
- ❖ Popular LLMs



# Basic Dataset Information

## *Strengths:*

- ❖ Dataset from Kaggle
- ❖ 11 comprehensive features and over 1500 entries
- ❖ Binary hiring decision feature to assist our model training
- ❖ Contains data that would be both ethical and unethical to use in hiring

## *Weaknesses:*

- ❖ Origins/motivations of data are not clear
- ❖ Uses scores that may not be practical for real companies to use

	Age	Gender	EducationLevel	ExperienceYears	PreviousCompanies	DistanceFromCompany
0	26	1	2	0	3	26.783828
1	39	1	4	12	3	25.862694
2	48	0	2	3	2	9.920805
3	34	1	2	5	2	6.407751
4	30	0	1	6	1	43.105343
5	27	0	3	14	4	31.706659
6	48	0	2	6	1	17.291229
7	40	0	4	13	3	10.586811
8	26	1	3	6	5	28.774864
9	45	1	2	2	5	30.195964

InterviewScore	SkillScore	PersonalityScore	RecruitmentStrategy	HiringDecision
48	78	91	1	1
35	68	80	2	1
20	67	13	2	0
36	27	70	3	0
23	52	85	2	0
54	50	50	1	1
24	52	64	3	0
6	3	92	3	0
80	78	51	1	1
92	16	94	3	0

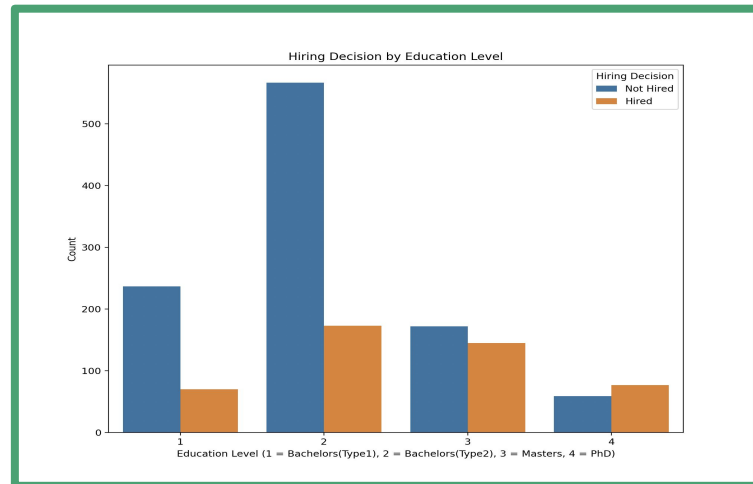
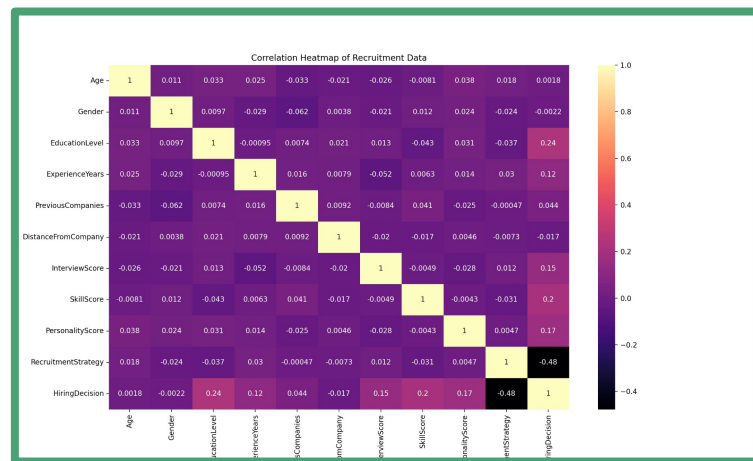
# Data Splitting + Cleaning

## Python Tools Used:

- ❖ Pandas, train\_test\_split, accuracy\_score, matplotlib

## Key Results:

- ❖ **Functional Datasets:** The split data is being properly used and is being currently improved to best aid models in learning and prediction accuracy
- ❖ **Visualization:** We see that education level is one of the most important features for predicting a hiring decision



# Neural Network Model Methods

## Model Architecture:

- ❖ Deep Neural Network: Input -> 64 -> 32 -> 16 neurons -> Output
- ❖ ReLU activation (hidden layers), Sigmoid activation (output layer) (output gives us a probability between 0 to 1)
- ❖ Dropout regularization (30%, 30%, 20%) to prevent overfitting

## Training Configuration

- ❖ Adam optimizer with binary cross entropy loss (Automatically adjusts learning rate for each parameter)
- ❖ 80/20 train-test split with 20% validation set (To test for overfitting during training)
- ❖ Early stopping: Stops training when validation loss stops improving for a certain number of epochs
- ❖ Reduces learning rate for faster and efficient convergence when learning is not improving
- ❖ Batch size: 32, Max epochs: 100

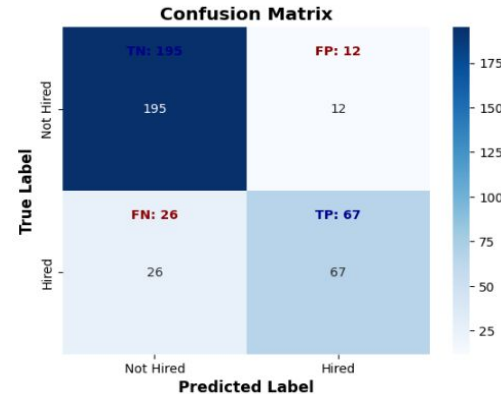
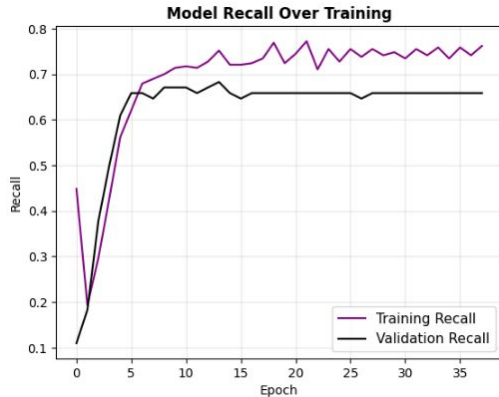
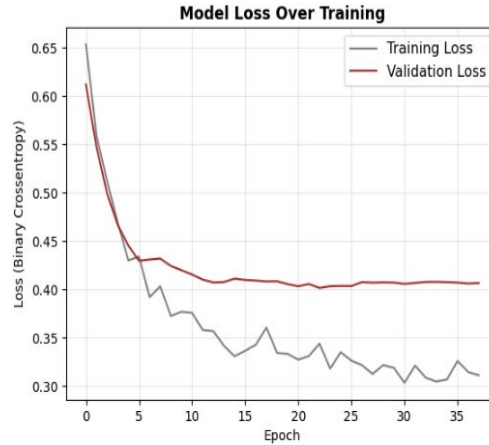
Layer (type)	Output Shape	Param #
hidden_layer_1 (Dense)	(None, 64)	704
dropout_1 (Dropout)	(None, 64)	0
hidden_layer_2 (Dense)	(None, 32)	2,080
dropout_2 (Dropout)	(None, 32)	0
hidden_layer_3 (Dense)	(None, 16)	528
dropout_3 (Dropout)	(None, 16)	0
output_layer (Dense)	(None, 1)	17

Total params: 3,329 (13.00 KB)

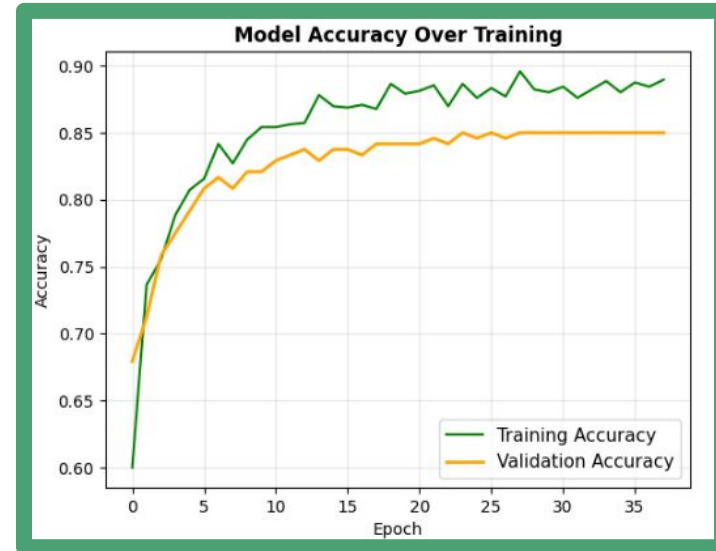
Trainable params: 3,329 (13.00 KB)

Non-trainable params: 0 (0.00 B)

# Neural Network Model Results



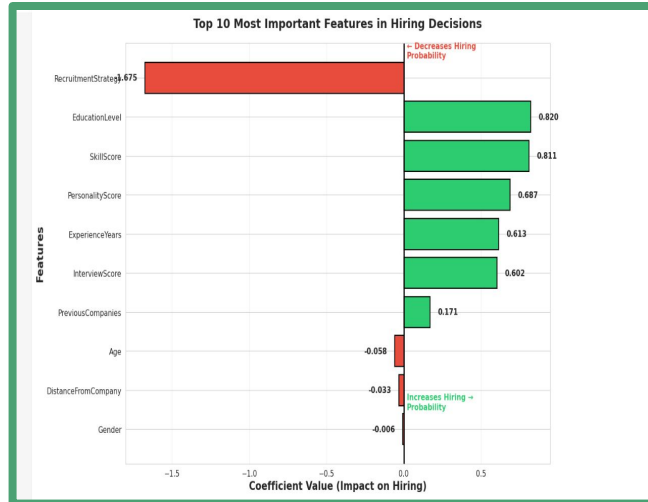
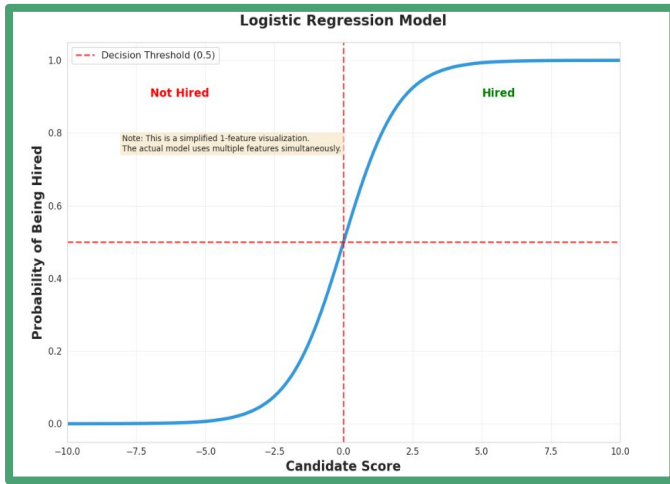
- ❖ Test Accuracy: 87.33%
- ❖ Precision: 84.81%
- ❖ Recall: 72.04%
- ❖ F1-Score: 0.7790
- ❖ ROC AUC: 0.8949
- ❖ Strong generalization with minimal overfitting



# Logistic Regression Model

## Brief Description:

- ❖ Logistic regression predicts hiring outcomes (hired/not hired) by calculating probabilities from candidate features using a sigmoid function.



## Python Tools Used:

- ❖ pandas, numpy, scikit-learn, matplotlib

## Key Results:

- ❖ Accuracy: **86.7%** (AUC = 0.905 - excellent discrimination)
- ❖ Top Predictors: EducationLevel (+0.82), SkillScore (+0.81), InterviewScore (+0.60)





# ChatGPT

- ❖ Model used: Random Forest Model
- ❖ Split training and testing data for quality analysis
- ❖ Prompts discouraged use of logistic regression or neural network models

## Classification Report

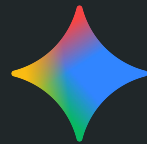
markdown

Copy code

	precision	recall	f1-score	support
... 300				
weighted avg	0.93	0.93	0.93	300

This indicates high performance across both classes with strong precision and recall.

# Gemini



- ❖ Model used: Gradient Boosting Classifier
- ❖ Also attempted random forest model, but had lower accuracy than ChatGPT
- ❖ Prompts discouraged use of logistic regression or neural network models

## Classification Report

Here is the performance breakdown for the Gradient Boosting model:

Class	Precision	Recall	F1-Score	Support
<b>Not Hired (0)</b>	0.92	0.98	0.95	207
<b>Hired (1)</b>	0.94	0.82	0.87	93
<b>Accuracy</b>			0.93	300

# Discussion of Results

Models ranked in order of accuracy  
(based on accuracy score):

1. Google Gemini's *Gradient Boosting Classifier* (**93%**, higher precision)
2. ChatGPT's *Random Forest Model* (**93%** , lower precision)
3. *Neural Network Model* (**87.3%**)
4. *Logistic Regression Model* (**86.7%**)

## *Exploring Further*

- ❖ According to the results, the data appears to be free from bias. Would any of these models be acceptable if it were trained with biased data?
  - ❖ What level of accuracy should a model have before being implemented in real hiring?
  - ❖ Which characteristics of a person's application should be taken into account by machine learning?
  - ❖ How can we hold models accountable to make sure they make accurate predictions and smart decisions?
-