Assignment 04

Regression Analysis in Pyspark

Tracy Anyasi

October 8, 2025

0.1 Generative AI Disclaimer

Generative AI (ChatGPT) was used to better understand the several dataframes created, their pipeline architecture, and debugging issues.

0.2 Github Repository Link

https://github.com/met-ad-688/assignment-04-tanyasiii

```
WARNING: Using incubator modules: jdk.incubator.vector
Using Spark's default log4j profile: org/apache/spark/log4j2-defaults.properties
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
25/10/05 23:28:39 WARN NativeCodeLoader: Unable to load native-hadoop library for your platfo
java classes where applicable
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---This is Diagnostic check, No need to print it in the final doc---
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25/10/05 23:28:56 WARN SparkStringUtils: Truncated the string representation of a plan since
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time (> 32 h...|                  2|                 2|       false|  NULL|         0|
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2051|Data Scientists|            23|Information Techn...|       231010|Business Intellig..
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|0cb072af26757b6c4...|        8/2/2024|  2024-08-02 17:08:...|        0|6/2/2024| 8/1/2024
time (> 32 h...|                  3|                 3|       false|  NULL|         1|
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2051|Data Scientists|            NULL|                   NULL|          56|Administrative an
|85318b12b3331fa49...|        9/6/2024|  2024-09-06 20:32:...|        1|6/2/2024| 7/7/2024
time (> 32 h...|                  5|               NULL|       false|  NULL|         0|
Fort Worth...|   48|     Texas|          48113|           Dallas, TX|          48113|
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|cb5ca25f02bdf25c1...|        6/19/2024|   2024-06-19 07:00:00|         0|6/2/2024|6/17/2024
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2051.01|Business Intellig...|15-2051.01|Business Intellig...|                  []|
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0.3 Feature Engineering

Remove incomplete data, keep relevant variables, and iron out complicated string values Encoder turns categorical columns (remote, hybrid, onsite) to numeric ones (1 or 0) based on input

```
from pyspark.sql.functions import col, pow, when
from pyspark.ml.feature import StringIndexer, VectorAssembler, OneHotEncoder
from pyspark.ml import Pipeline

#remove rows with NAs
df_cleaned = df.dropna(subset=[
    "SALARY", "MIN_YEARS_EXPERIENCE", "STATE_NAME", "EMPLOYMENT_TYPE_NAME",
    "REMOTE_TYPE_NAME", "MIN_EDULEVELS_NAME", "DURATION",
    "IS_INTERNSHIP", "COMPANY_IS_STAFFING"
])

eda_cols = [
    "SALARY", "MIN_YEARS_EXPERIENCE", "DURATION", "COMPANY_IS_STAFFING",
    "IS_INTERNSHIP", "STATE_NAME", "REMOTE_TYPE_NAME",
    "EMPLOYMENT_TYPE_NAME", "MIN_EDULEVELS_NAME"
]
df_cleaned = df_cleaned.select(eda_cols)

#clean up REMOTE_TYPE_NAME and reduce the different inputs
df_cleaned = df_cleaned.withColumn(
    "REMOTE_TYPE_NAME",
    when(col("REMOTE_TYPE_NAME") == "Remote", "Remote")
    .when(col("REMOTE_TYPE_NAME") == "[None]", "Undefined")
    .when(col("REMOTE_TYPE_NAME") == "Not Remote", "On Premise")
    .when(col("REMOTE_TYPE_NAME") == "Hybrid Remote", "Hybrid")
    .when(col("REMOTE_TYPE_NAME").isNull(), "On Premise")
    .otherwise(col("REMOTE_TYPE_NAME"))
)

#clean EMPLOYMENT_TYPE_NAME
df_cleaned = df_cleaned.withColumn(
    "EMPLOYMENT_TYPE_NAME",
    when(col("EMPLOYMENT_TYPE_NAME") == "Part-time / full-time", "Flexible")
    .when(col("EMPLOYMENT_TYPE_NAME") == "Part-time (â‰¤ 32 hours)", "Parttime")
    .when(col("EMPLOYMENT_TYPE_NAME") == "Full-time (> 32 hours)", "Fulltime")
    .when(col("EMPLOYMENT_TYPE_NAME").isNull(), "Fulltime")
    .otherwise(col("EMPLOYMENT_TYPE_NAME"))
```

```
)

#df_cleaned = df_cleaned.filter(col("REMOTE_TYPE_NAME") != "Undefined") -- initially wnated t
#percentage of the regression model

# Categorical and numeric columns
categorical_cols = ["EMPLOYMENT_TYPE_NAME", "REMOTE_TYPE_NAME"]
continuous_cols = ["MIN_YEARS_EXPERIENCE", "DURATION", "IS_INTERNSHIP", "COMPANY_IS_STAFFING"

# Index and One-Hot Encode
indexers = [StringIndexer(inputCol=col, outputCol=f"{col}_Idx", handleInvalid="skip") for col
encoders = [OneHotEncoder(inputCol=f"{col}_Idx", outputCol=f"{col}_vec") for col in categori
```

```
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|SALARY|features                               |features_poly                               |
+------+---------------------------------------+--------------------------------------------
+
|192800|(9,[0,1,4,6],[6.0,55.0,1.0,1.0])       |(10,[0,1,4,6,9],[6.0,55.0,1.0,1.0,36.0])    |
|125900|(9,[0,1,4,6],[12.0,18.0,1.0,1.0])      |(10,[0,1,4,6,9],[12.0,18.0,1.0,1.0,144.0])  |
|118560|[5.0,20.0,0.0,1.0,1.0,0.0,0.0,1.0,0.0]|[5.0,20.0,0.0,1.0,1.0,0.0,0.0,1.0,0.0,25.0]|
|192800|(9,[0,1,4,6],[6.0,55.0,1.0,1.0])       |(10,[0,1,4,6,9],[6.0,55.0,1.0,1.0,36.0])    |
|116500|(9,[0,1,4,6],[12.0,16.0,1.0,1.0])      |(10,[0,1,4,6,9],[12.0,16.0,1.0,1.0,144.0])  |
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only showing top 5 rows
```

```
Mapping for EMPLOYMENT_TYPE_NAME:
  Index 0 -> Fulltime
  Index 1 -> Parttime
  Index 2 -> Flexible

[Stage 22:>                                                         (0 + 1) / 1]
```

```
Mapping for REMOTE_TYPE_NAME:
  Index 0 -> Undefined
  Index 1 -> Remote
  Index 2 -> Hybrid
  Index 3 -> On Premise
```

0.4 Linear Regression

```
25/10/05 23:29:25 WARN Instrumentation: [68f324e3] regParam is zero, which might cause numer
[Stage 32:>                                                         (0 + 1) / 1]

R² Score: 0.2840
RMSE: 35315.94
MAE: 27676.61




Coefficient Summary:
                 Feature      Estimate    Std Error     t-Stat       p-
Value  \
0              Intercept  76735.577948   102.356000  66.277489  0.000000e+00
1    MIN_YEARS_EXPERIENCE   6783.898664    23.632630  -1.831651  6.702934e-02
2               DURATION    -43.286721  6866.446762  -1.025459  3.051684e-01
3          IS_INTERNSHIP  -7041.257613  1063.265929  -0.595172  5.517402e-01
4     COMPANY_IS_STAFFING   -632.826152  3011.540238  -0.421858  6.731367e-01
5  EMPLOYMENT_TYPE_NAME_A  -1270.441524  3605.833255  -1.077711  2.811853e-01
6  EMPLOYMENT_TYPE_NAME_B  -3886.046755  2462.498142   3.306373  9.480161e-04
7      REMOTE_TYPE_NAME_X   8141.937756  2529.947825   3.635882  2.782402e-04
8      REMOTE_TYPE_NAME_Y   9198.592476  3172.252546   7.636575  2.398082e-14
9      REMOTE_TYPE_NAME_Z  24225.144004  3579.670705  21.436491  0.000000e+00

   95% CI Lower  95% CI Upper
0  76534.942765  76936.213130
1   6737.574686   6830.222643
2 -13502.691172  13416.117730
3  -9125.439821  -4957.075405
4  -6535.957638   5270.305334
```

```
5   -8338.488484   5797.605435
6   -8712.962276    940.868767
7    3182.809376  13101.066136
8    2980.437509  15416.747443
9   17208.380095  31241.907914
```

The linear regression model explains approximately 28% of the variance in salaries, showing that while job attributes like as experience and remote status influence pay, substantial variation remains unexplained. This is likely due to qualitative factors like role seniority, company size, or negotiation effects. Undefined roles were initally excluded but that reduced the model's reliabilty and was subsequentially added as a baseline for remote roles.

Some statistically significant predictors include remote and hybrid roles (Remote Type X & Y) and Flexible employment type, all of which show clear positive or negative salary impacts. Compared to the baseline groups (Fulltime employment and Undefined remote), Flexible roles pay significantly less than Fulltime roles, whereas Parttime roles do not show a significant difference. For remote types, Remote, Hybrid, and On Premise roles show meaningful salary increases relative to Undefined roles, with On Premise roles exhibiting the largest premium of approximately $24K.

Non-significant coefficients, such as Parttime or certain remote categories, suggest that observed differences may be due to random variation rather than a true effect, while the significant predictors highlight areas where job structure meaningfully affects compensation.

0.5 Polynominal Linear Regression

```
25/10/05 23:29:51 WARN Instrumentation: [48c15026] regParam is zero, which might cause numer
```

```
                  Feature   Coefficient    Std Error    t-value  \
0               Intercept  67932.172201   365.427981  34.124107
1      MIN_YEARS_EXPERIENCE  12469.903484    23.369295  -1.746680
2   MIN_YEARS_EXPERIENCE_SQ    -40.818670  6795.398159  -0.378451
3                DURATION  -2571.726155  1051.916215  -1.110934
4           IS_INTERNSHIP  -1168.609779  2990.337025  -1.899043
5       COMPANY_IS_STAFFING  -5678.777125  3572.973249  -2.128946
6     EMPLOYMENT_TYPE_NAME_A  -7606.667528  2435.260898   3.109557
7     EMPLOYMENT_TYPE_NAME_B   7572.582266  2501.762396   3.565968
8         REMOTE_TYPE_NAME_X   8921.205741  3137.964205   7.286182
9         REMOTE_TYPE_NAME_Y  22863.778828    26.275186 -16.193368
10        REMOTE_TYPE_NAME_Z   -425.483749  3581.211738  18.969047
```

```
       p-value  95% CI Lower  95% CI Upper
0   0.000000e+00  67215.871148  68648.473253
1   8.071963e-02  12424.095687  12515.711281
2   7.051025e-01 -13360.955886  13279.318546
3   2.666199e-01  -4633.661011   -509.791298
4   5.758388e-02  -7030.179413   4692.959856
5   3.327990e-02 -12682.412944   1324.858694
6   1.878259e-03 -12380.193459  -2833.141596
7   3.639866e-04   2668.702078  12476.462454
8   3.397282e-13   2770.261704  15072.149779
9   0.000000e+00  22812.274990  22915.282666
10  0.000000e+00  -7445.268409   6594.300910

[Stage 37:>                                                         (0 + 1) / 1]

Polynomial Regression R²: 0.3016947273606302
Polynomial Regression RMSE: 34875.92736404874
Polynomial Regression MAE: 27190.399586682357
```

The polynomial regression model explains about 30% of the variance in salaries, showing that experience and job attributes influence pay, though much variation still remains unexplained. Significant predictors include remote and hybrid roles and all employment types meaningfully impact salaries.

Non-significant terms with limited contributions, such as the quadratic minimum years of experience term, has a negative coefficient while the linear minimum years of experience is positive, suggesting that althought salary increaes with more experience, the increase slows down as experience grows and plateaus. Overall, the model highlights which job characteristics most strongly affect compensation while capturing some non-linear effects of experience.

0.6 Random Forest Regressor

```
25/10/05 23:30:40 WARN DAGScheduler: Broadcasting large task binary with size 1210.5 KiB
25/10/05 23:30:43 WARN DAGScheduler: Broadcasting large task binary with size 2.1 MiB
25/10/05 23:30:48 WARN DAGScheduler: Broadcasting large task binary with size 3.7 MiB
25/10/05 23:30:55 WARN DAGScheduler: Broadcasting large task binary with size 6.1 MiB
25/10/05 23:31:01 WARN DAGScheduler: Broadcasting large task binary with size 1402.3 KiB
[Stage 56:>                                                         (0 + 1) / 1]
```

```
+------+------------------+
|SALARY|        prediction|
+------+------------------+
| 29120|114624.66663326925|
| 31200| 96687.65499926287|
| 31200|114624.66663326925|
| 31640| 96228.91630692781|
| 32240| 95844.37906654779|
+------+------------------+
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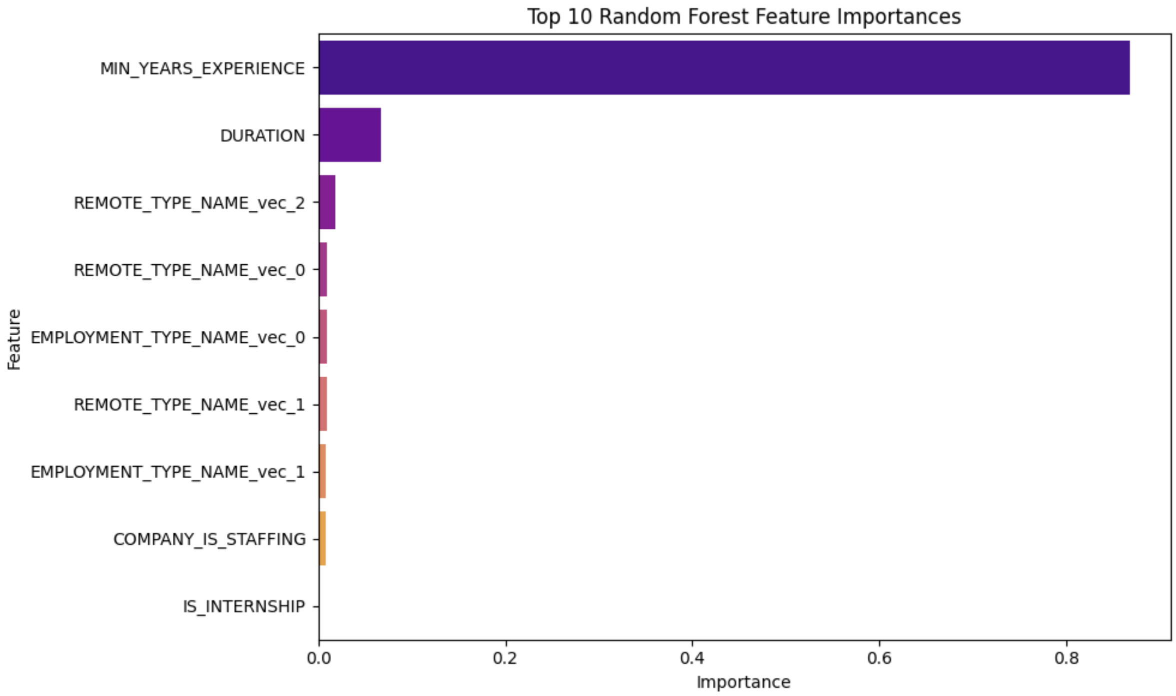
Feature Importances: [np.float64(0.8681171759565247), np.float64(0.06743212825429395), np.flo
```

1 Feature Importance Plot

```
/tmp/ipykernel_1623/862456364.py:36: FutureWarning:

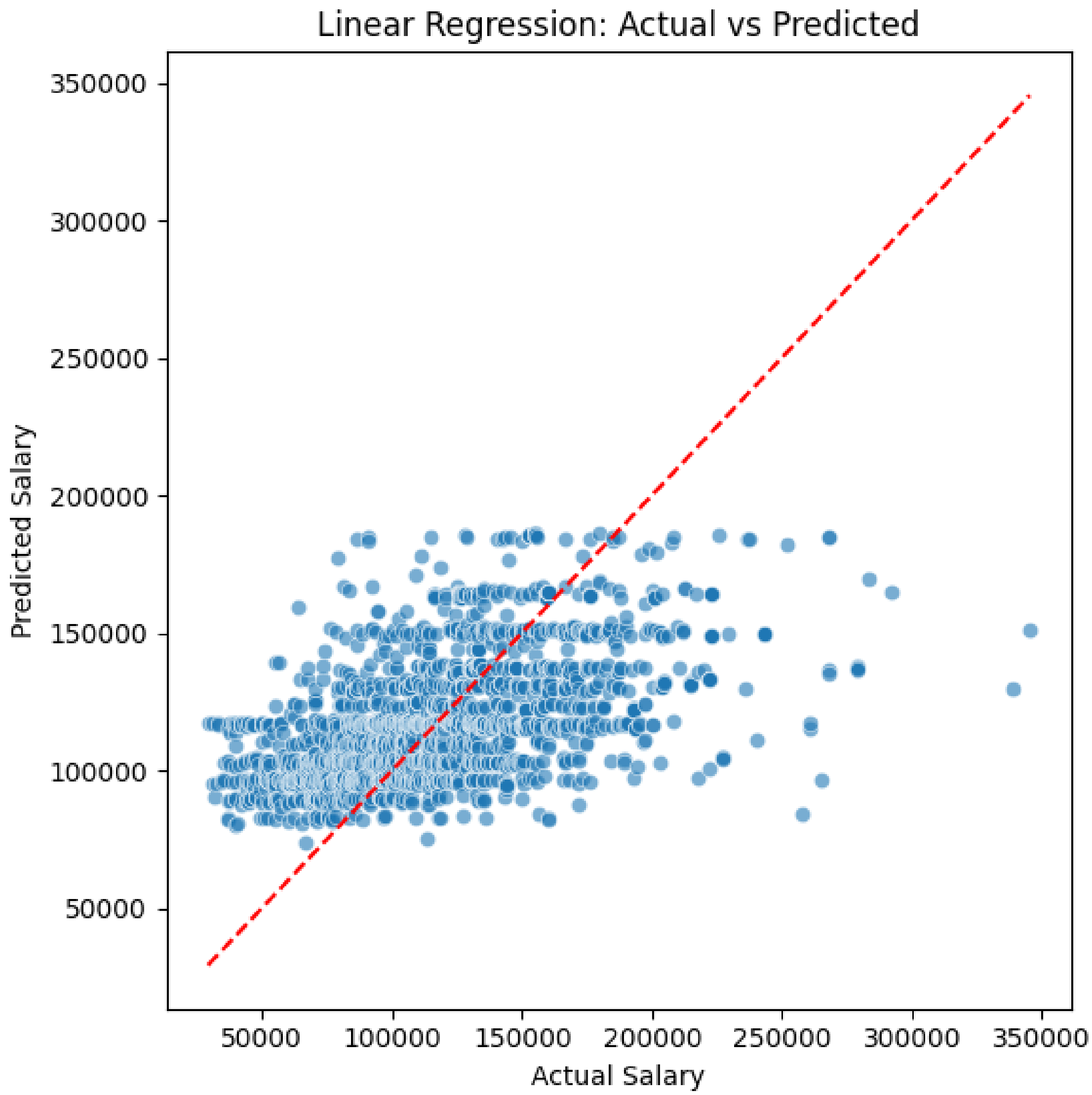


Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assig
```



This highlights that minimum years of experience has the most importance in predicating salary in roles compared to other features.

1.1 Comparing the 3 Model - Generalized Linear, Polynomial, and Random Forest


Linear Regression: Actual vs Predicted
Predicted Salary
Actual Salary
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300000
250000
200000
150000
100000
50000
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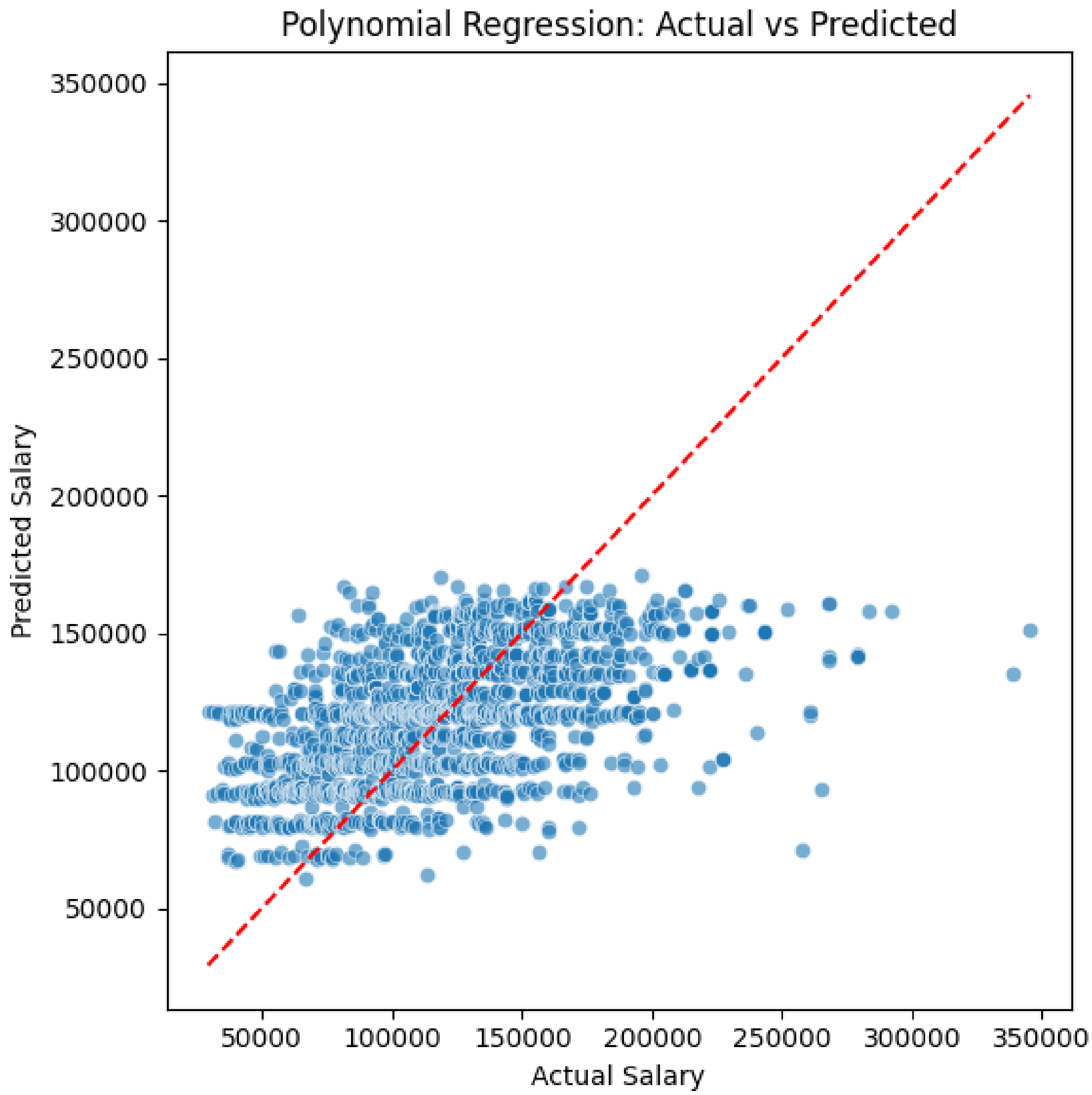
100000
150000
200000
250000
300000
350000


Polynomial Regression: Actual vs Predicted
Predicted Salary
Actual Salary
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300000
250000
200000
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100000
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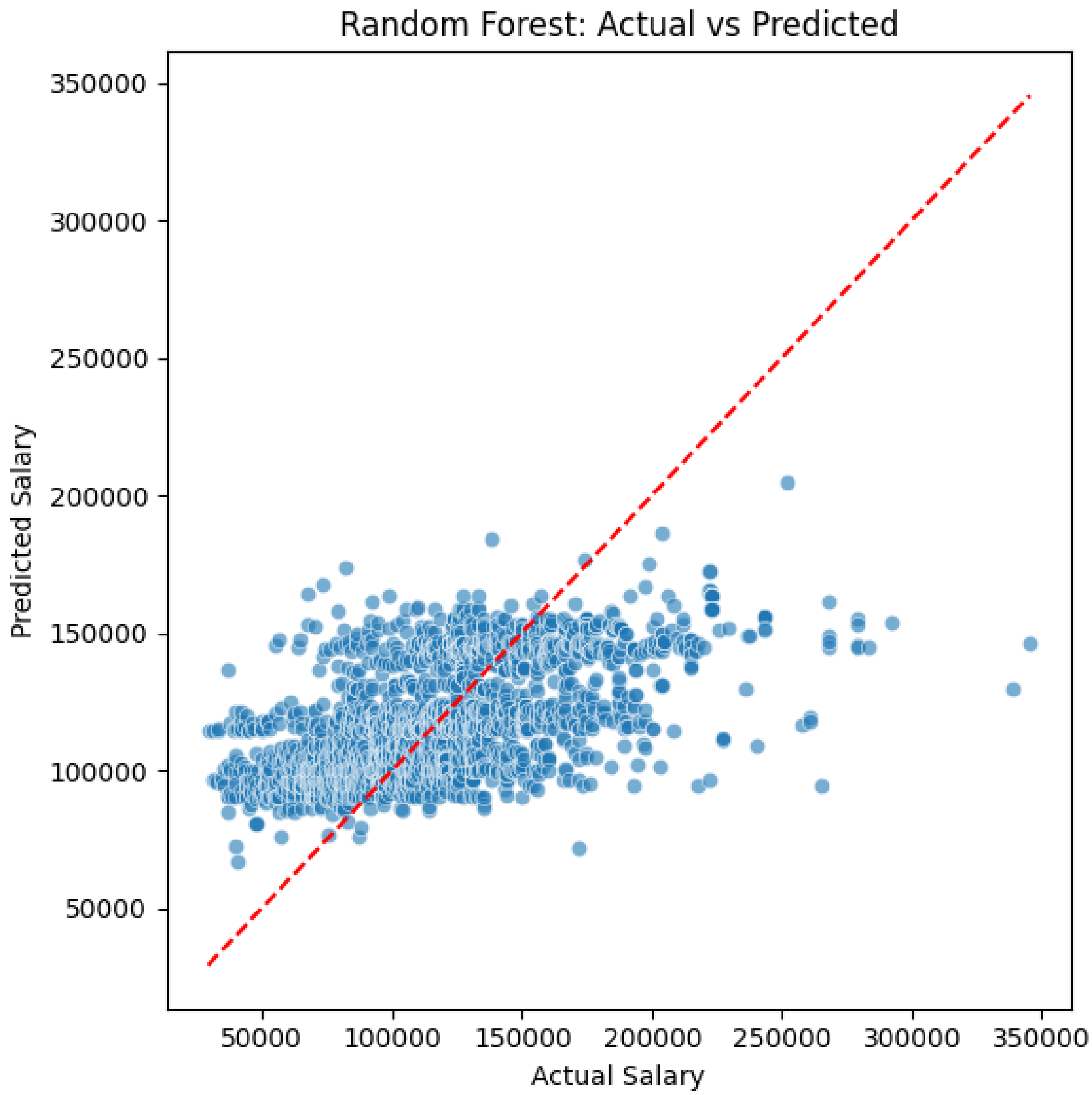
150000
200000
250000
300000
350000




```
RMSE - Linear Regression: 32433.87
RMSE - Polynomial Regression: 30897.99
RMSE - Random Forest: 24941.84
```

```
AIC - Linear Regression: 60941.54
AIC - Polynomial Regression: 60878.13
```

```
[Stage 145:>                                                        (0 + 1) / 1]

BIC - Linear Regression: 84857.93
BIC - Polynomial Regression: 84584.34
BIC - Random Forest (approx.): 86841.66
```

Random Forest provides the most accurate salary predictions, achieving the lowest RMSE (24,942), while polynomial regression improves over linear regression (30,898 vs 32,434) by capturing simple nonlinear effects.

In terms of model fit, polynomial regression shows slightly better AIC and BIC values than linear regression, indicating it balances complexity and explanatory power. Random Forest, despite a higher approximate BIC due to its complexity, outperforms both parametric models in prediction, highlighting its ability to capture complex feature interactions.

Overall, Random Forest is best for predictive performance, whereas polynomial regression offers a reasonable trade-off between fit and interpretability.