

# Assignment 03

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## 1 Import Dataset

```
import pandas as pd
import plotly.express as px
import plotly.io as pio
from pyspark.sql import SparkSession
import re
import numpy as np
import plotly.graph_objects as go
from pyspark.sql.functions import col, split, explode, regexp_replace, transform, when
from pyspark.sql import functions as F
from pyspark.sql.functions import col, monotonically_increasing_id

np.random.seed(42)
#pio.renderers.default = "vscode+notebook+svg"

spark = SparkSession.builder.appName("LightcastData").getOrCreate()
df = (
    spark.read
        .option("header", "true")
        .option("inferSchema", "true")
        .option("multiLine", "true")
        .option("escape", "\\")
        .csv("lightcast_job_postings.csv")
)
```

```
df.createOrReplaceTempView("job_postings")
#df.show(5)
```

[Stage 14:>

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## 2 Casting salary and experience columns

### 2.1 Computing medians and Imputing missing salaries

```
from pyspark.sql.functions import col

df = df.withColumn("SALARY", col("SALARY").cast("float")) \
        .withColumn("SALARY_FROM", col("SALARY_FROM").cast("float")) \
        .withColumn("SALARY_TO", col("SALARY_TO").cast("float")) \
        .withColumn("MIN_YEARS_EXPERIENCE", col("MIN_YEARS_EXPERIENCE").cast("float")) \
        .withColumn("MAX_YEARS_EXPERIENCE", col("MAX_YEARS_EXPERIENCE").cast("float"))

# Computing medians for salary columns
def compute_median(sdf, col_name):
    return sdf.approxQuantile(col_name, [0.5], 0.01)[0]

median_from = compute_median(df, "SALARY_FROM")
median_to = compute_median(df, "SALARY_TO")
median_salary = compute_median(df, "SALARY")

print("Medians:", median_from, median_to, median_salary)

# Imputing missing salaries, but not experience
df = df.fillna({
    "SALARY_FROM": median_from,
    "SALARY_TO": median_to
})

# Computing average salary
df = df.withColumn(
    "Average_Salary", (col("SALARY_FROM") + col("SALARY_TO")) / 2
```

```

)

# Selecting required columns
export_cols = [
    "Average_Salary",
    "SALARY",
    "EDUCATION_LEVELS_NAME",
    "REMOTE_TYPE_NAME",
    "MAX_YEARS_EXPERIENCE",
    "LOT_V6_SPECIALIZED_OCCUPATION_NAME"
]

df_selected = df.select(*export_cols)

pdf_selected = df_selected.toPandas()
pdf_selected.head()

```

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Medians: 87295.0 130042.0 115024.0

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	Average_Salary	SALARY	EDUCATION_LEVELS_NAME	REMOTE_TYPE_NAME	MAX_YEARS_EXPERIENCE	LOT_V6_SPECIALIZED_OCCUPATION_NAME
0	108668.5	NaN	[\n "Bachelor's degree"\n]	[None]	2.0	General ERP Analyst /
1	108668.5	NaN	[\n "No Education Listed"\n]	Remote	3.0	Oracle Consultant / An
2	108668.5	NaN	[\n "Bachelor's degree"\n]	[None]	NaN	Data Analyst
3	108668.5	NaN	[\n "No Education Listed"\n]	[None]	NaN	Data Analyst
4	92500.0	92500.0	[\n "No Education Listed"\n]	[None]	NaN	Oracle Consultant / An

## 2.2 Cleaning Education column and Exporting Cleaned Data

\*I referred to Claude Sonnet 4 for prompts and sample code ideas, but I wrote and adapted the final implementation myself

```
# To remove \n and \r
pdf_selected["EDUCATION_LEVELS_NAME"] = (
    pdf_selected["EDUCATION_LEVELS_NAME"]
    .astype(str)
    .str.replace(r"[\n\r]", "", regex=True)
    .str.strip()
)
pdf_selected.to_csv("data/lightcast_cleaned.csv", index=False)
pdf_selected.head()
```

	Average_Salary	SALARY	EDUCATION_LEVELS_NAME	REMOTE_TYPE_NAME	MAX_YEARS_EXPERIENCE	LOT_V6_SPECIALIZ
0	108668.5	NaN	[ "Bachelor's degree"]	[None]	2.0	General ERP Analyst /
1	108668.5	NaN	[ "No Education Listed"]	Remote	3.0	Oracle Consultant / An
2	108668.5	NaN	[ "Bachelor's degree"]	[None]	NaN	Data Analyst
3	108668.5	NaN	[ "No Education Listed"]	[None]	NaN	Data Analyst
4	92500.0	92500.0	[ "No Education Listed"]	[None]	NaN	Oracle Consultant / An

## 2.3 Exporting Cleaned Data

```
print("Data cleaning complete. Rows retained:", len(pdf_selected))
```

Data cleaning complete. Rows retained: 72498

## 3 Salary Distribution by Industry and Employment Type

### 3.1 Salary Distribution by Employment Type

```
pdf = df.select(
    "EMPLOYMENT_TYPE_NAME",
    "NAICS2_NAME",
    "SALARY"
).toPandas()
```

```
pdf = pdf[pdf["SALARY"] > 0]

pdf["EMPLOYMENT_TYPE_NAME"] = (
    pdf["EMPLOYMENT_TYPE_NAME"]
    .astype(str)
    .apply(lambda x: re.sub(r"^\x00-\x7F+", "", x))
    .str.strip()
)

median_salaries = pdf.groupby("EMPLOYMENT_TYPE_NAME")["SALARY"].median()

sorted_employment_types = median_salaries.sort_values(ascending=False).index

pdf["EMPLOYMENT_TYPE_NAME"] = pd.Categorical(
    pdf["EMPLOYMENT_TYPE_NAME"],
    categories=sorted_employment_types,
    ordered=True
)
```

[Stage 19:>

(0 + 1) / 1]

```
fig = px.box(
    pdf,
    x="EMPLOYMENT_TYPE_NAME",
    y="SALARY",
    title="Salary Distribution by Employment Type",
    color_discrete_sequence=["#CC0000"],
    boxmode="group",
    points="outliers"
)

fig.update_layout(
    xaxis=dict(
        title=dict(
            text="Employment Type",
            font=dict(size=14, family="Arial Black", color="black")
        ),
    ),
```

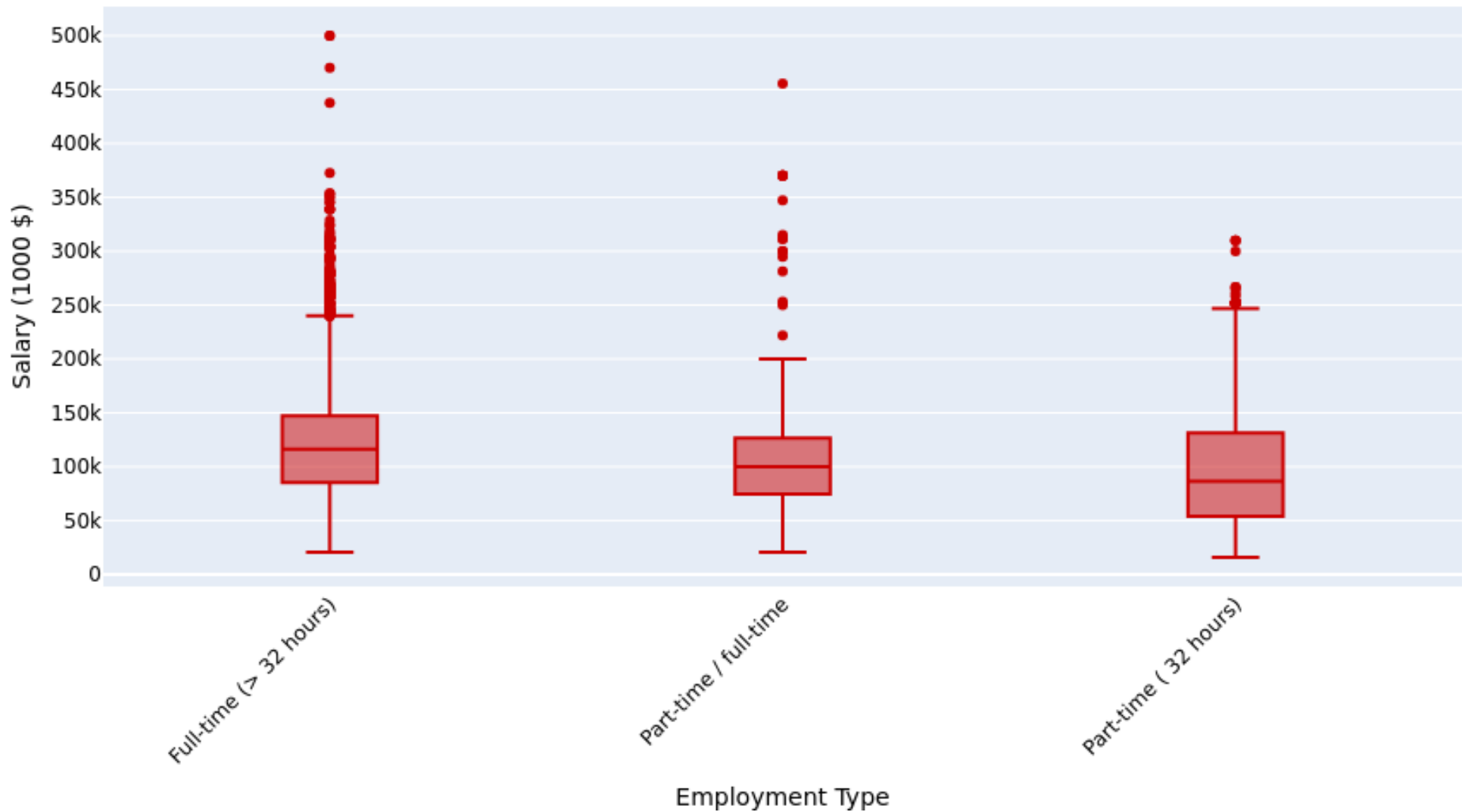
```

        tickangle=-45,
        tickfont=dict(size=12, family="Arial Black", color="black"),
        categoryorder="array",
        categoryarray=sorted_employment_types.tolist()
    ),
    yaxis=dict(
        title=dict(
            text="Salary (1000 $)",
            font=dict(size=14, family="Arial Black", color="black")
        ),
        tickvals=[0, 50000, 100000, 150000, 200000, 250000, 300000, 350000, 400000, 450000, 500000],
        ticktext=["0", "50k", "100k", "150k", "200k", "250k", "300k", "350k", "400k", "450k", "500k"],
        tickfont=dict(size=12, family="Arial Black", color="black"),
    ),
    font=dict(family="Arial", size=16, color="black"),
    boxgap=0.7,
    showlegend=False,
    height=500,
    width=850,
)

fig.write_html("./output/Q1.html")
fig.write_image("./output/Q1.png", width = 850, height = 500, scale=1)

```

## Salary Distribution by Employment Type



### 3.1.1 Interpretation

- The boxplot indicates that full-time employees (>32 hours) receive higher median salaries with greater variability.
- In contrast, part-time employees indicates lower and more consistent salary ranges, with occasional high outliers

## 3.2 Salary Distribution by Industry

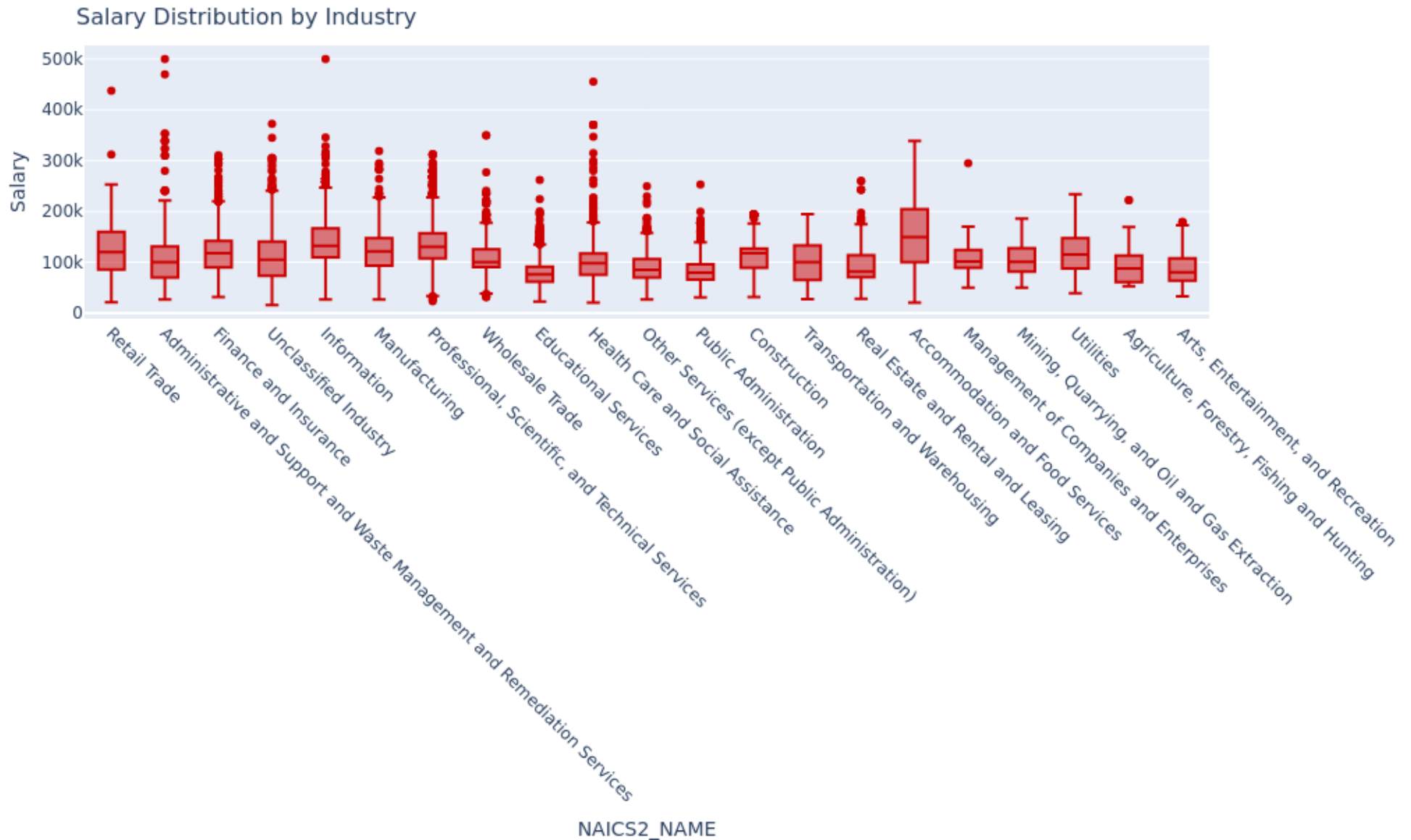
```
pdf = df.select(
    "NAICS2_NAME",
    "SALARY"
).toPandas()

fig = px.box(
    pdf,
    x="NAICS2_NAME",
    y="SALARY",
    title="Salary Distribution by Industry",
    color_discrete_sequence=["#CC0000"],
    points="outliers"
)

fig.update_layout(
    height=500,
    font_family="Arial",
    title_font_size=16,
    xaxis_title="NAICS2_NAME",
    yaxis_title="Salary",
    xaxis_tickangle=45,
)

fig.write_html("./output/Q2.html")
fig.write_image("./output/Q2.png", width=1000, height=600, scale=1)
```





### 3.2.1 Interpretation

- The boxplot indicates that salary levels differ across industries, with Information, Finance, and Professional Services showing higher median salaries. \*Education and Public Administration have lower median salaries with narrower ranges.
- Most industries center around \$100k, though some display wider variation and notable outliers.

## 4 Salary Analysis by ONET Occupation Type (Bubble Chart)

```
salary_analysis = spark.sql("""
SELECT
    LOT_OCCUPATION_NAME AS Occupation_Name,
    PERCENTILE(SALARY, 0.5) AS Median_Salary,
    COUNT(*) AS Job_Postings
FROM job_postings
GROUP BY LOT_OCCUPATION_NAME
ORDER BY Job_Postings DESC
LIMIT 10
""")

salary_pd = salary_analysis.toPandas()
salary_pd.head()
```

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	Occupation_Name	Median_Salary	Job_Postings
0	Data / Data Mining Analyst	95250.0	30057
1	Business Intelligence Analyst	125900.0	29445
2	Computer Systems Engineer / Architect	157600.0	8212
3	Business / Management Analyst	93650.0	4326
4	Clinical Analyst / Clinical Documentation and ...	89440.0	261

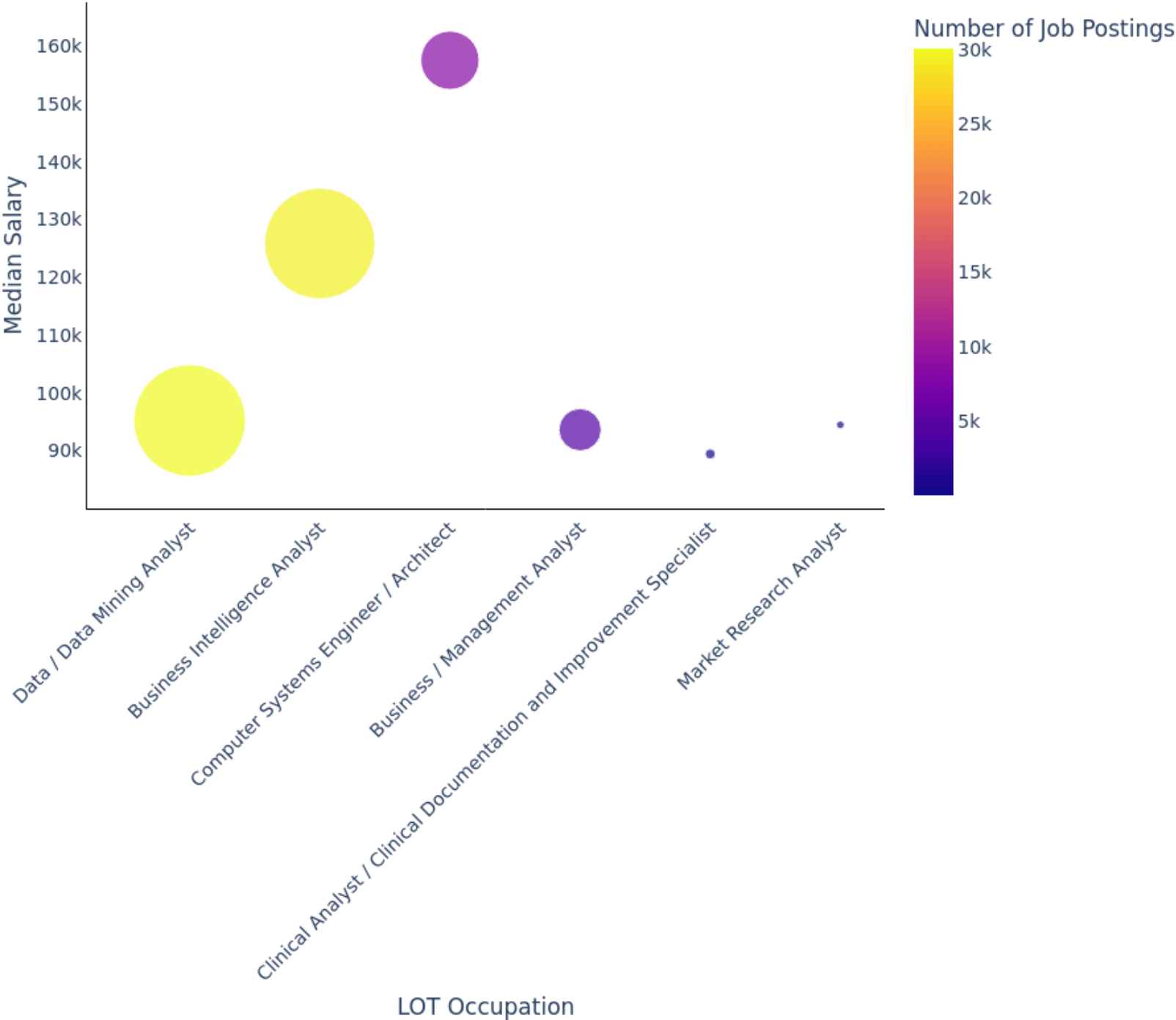
```
fig = px.scatter(
    salary_pd,
    x="Occupation_Name",
    y="Median_Salary",
    size="Job_Postings",
    title="Salary Analysis by LOT Occupation Type (Bubble Chart)",
    labels={
        "Occupation_Name": "LOT Occupation",
        "Median_Salary": "Median Salary",
        "Job_Postings": "Number of Job Postings",
    },
)
```

```
    hover_name="Occupation_Name",
    size_max=60,
    width=900,
    height=800,
    color="Job_Postings",
    color_continuous_scale="Plasma",
)

fig.update_layout(
    font_family="Arial",
    font_size=14,
    title_font_size=22,
    xaxis_title="LOT Occupation",
    yaxis_title="Median Salary",
    plot_bgcolor="white",
    xaxis=dict(
        tickangle=-45,
        showline=True,
        linecolor="black",
    ),
    yaxis=dict(
        showline=True,
        linecolor="black",
    ),
)

fig.write_html("./output/Q3.html")
fig.write_image("./output/Q3.png", width=900, height=800, scale=1)
```

Salary Analysis by LOT Occupation Type (Bubble Chart)



## 4.1 Interpretation

- The chart demonstrates that Business Intelligence Analysts and Data/Data Mining Analysts have the largest number of job postings but only moderate median salaries.
- Computer Systems Engineers/Architects earn the highest median salaries but with fewer postings.
- Overall, this indicates that high demand does not always align with the highest pay.

## 5 Salary by Education Level

```
from pyspark.sql.functions import col, when

df = df.withColumn(
    "EDU_GROUP",
    when(col("EDUCATION_LEVELS_NAME").rlike("(?i)Associate|GED|No Education Listed|Highschool"), "Associate or Lower")
    .when(col("EDUCATION_LEVELS_NAME").rlike("(?i)Bachelor"), "Bachelor")
    .when(col("EDUCATION_LEVELS_NAME").rlike("(?i)Master"), "Master's")
    .when(col("EDUCATION_LEVELS_NAME").rlike("(?i)PhD|Doctorate|professional degree"), "PhD")
    .otherwise(None)
)

df = df.withColumn("MAX_YEARS_EXPERIENCE", col("MAX_YEARS_EXPERIENCE").cast("float"))
df = df.withColumn("Average_Salary", col("Average_Salary").cast("float"))

df = df.filter(
    col("MAX_YEARS_EXPERIENCE").isNotNull() &
    (col("MAX_YEARS_EXPERIENCE") > 0) &
    col("Average_Salary").isNotNull() &
    (col("Average_Salary") > 0)
)

df_selected = df.select(
    col("MAX_YEARS_EXPERIENCE").alias("MAX_EXPERIENCE"),
    col("Average_Salary").alias("AVERAGE_SALARY"),
    col("EDU_GROUP"),
    col("LOT_V6_SPECIALIZED_OCCUPATION_NAME").alias("OCCUPATION_NAME")
)
```

```
df_pd = df_selected.toPandas()
```

```
df_pd.head()
```

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	MAX_EXPERIENCE	AVERAGE_SALARY	EDU_GROUP	OCCUPATION_NAME
0	2.0	108668.5	Bachelor	General ERP Analyst / Consultant
1	3.0	108668.5	Associate or Lower	Oracle Consultant / Analyst
2	7.0	108668.5	Associate or Lower	General ERP Analyst / Consultant
3	2.0	92962.0	Bachelor	Data Analyst
4	5.0	108668.5	Associate or Lower	Data Analyst

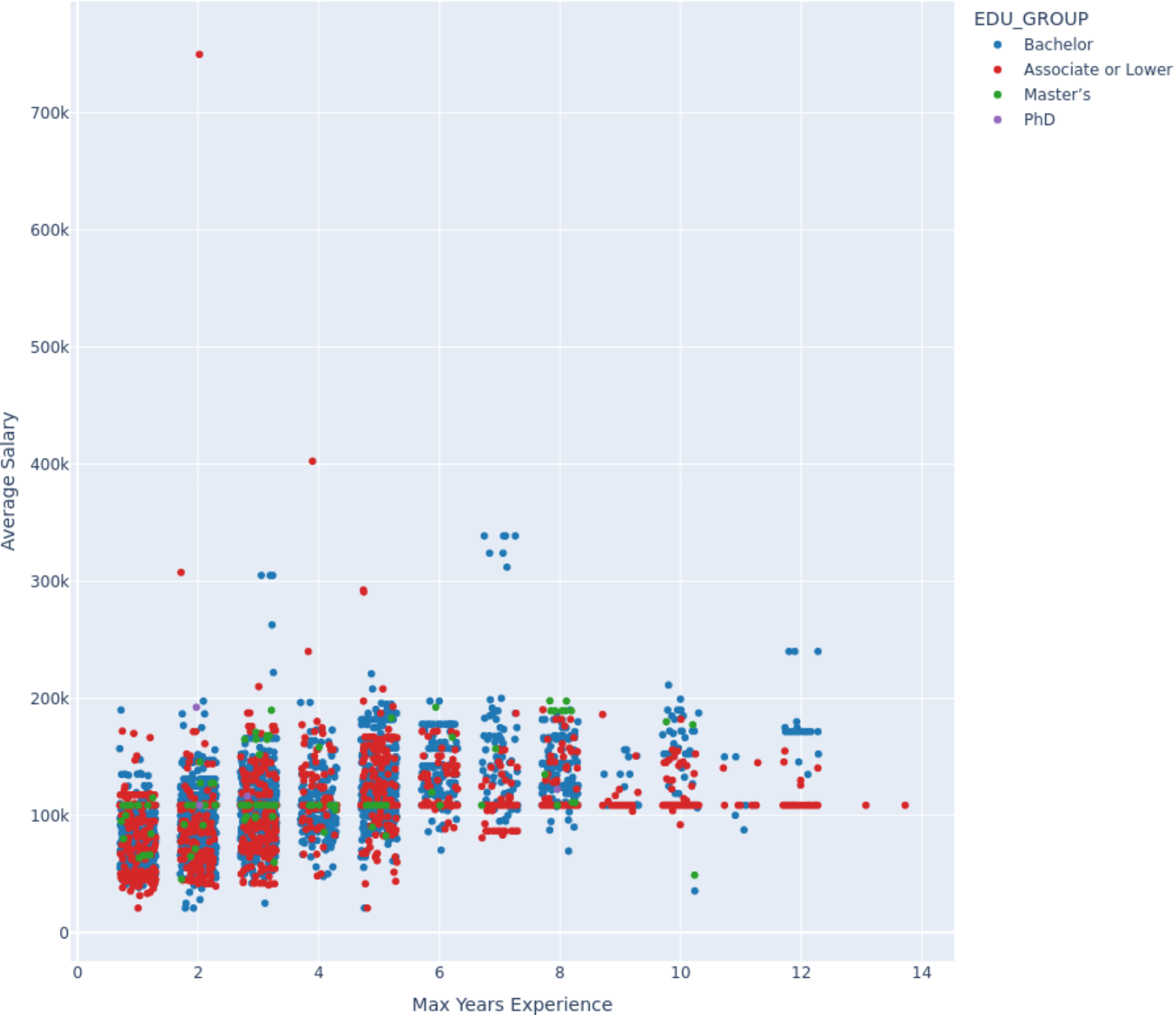
```
np.random.seed(42)
df_pd["MAX_EXPERIENCE_JITTER"] = (
    df_pd["MAX_EXPERIENCE"] + np.random.uniform(-0.3, 0.3, len(df_pd))
)
```

```
fig = px.scatter(
    df_pd,
    x="MAX_EXPERIENCE_JITTER",
    y="AVERAGE_SALARY",
    color="EDU_GROUP",
    hover_data=["OCCUPATION_NAME", "MAX_EXPERIENCE", "AVERAGE_SALARY"],
    title="Salary vs Experience by Education Level",
    color_discrete_map = {
        "Bachelor": "#1f77b4",
        "Associate or Lower": "#d62728",
        "Master's": "#2ca02c",
        "PhD": "#9467bd"
    }
)
```

```
fig.update_layout(
    xaxis_title="Max Years Experience",
    yaxis_title="Average Salary",
)
```

```
width=1000,  
height=600,  
font_family="Arial",  
title_font_size=16  
)  
  
fig.write_html("./output/Q4.html")  
fig.write_image("./output/Q4.png", width=900, height=800, scale=1)
```

Salary vs Experience by Education Level





## 5.1 Interpretation

- Salaries tend to increase with years of experience, though variation exists across education levels.
- PhD and Master's degree holders generally earn the highest salaries, while Associate or lower groups comparatively earn less.

## 6 Salary by Remote Work Type

```
from pyspark.sql.functions import col, when, lower, trim

df = df.withColumn(
    "REMOTE_GROUP",
    when(lower(trim(col("REMOTE_TYPE_NAME"))).rlike("hyb|mix|partial|split|combo"), "Hybrid")
    .when(lower(trim(col("REMOTE_TYPE_NAME"))).rlike("remote|wfh|home|tele"), "Remote")
    .otherwise("Onsite")
)

df = df.withColumn("MAX_YEARS_EXPERIENCE", col("MAX_YEARS_EXPERIENCE").cast("float"))
df = df.withColumn("Average_Salary", col("Average_Salary").cast("float"))

df = df.filter(
    col("MAX_YEARS_EXPERIENCE").isNotNull() &
    (col("MAX_YEARS_EXPERIENCE") > 0) &
    col("Average_Salary").isNotNull() &
    (col("Average_Salary") > 0)
)

df_selected = df.select(
    col("MAX_YEARS_EXPERIENCE").alias("MAX_EXPERIENCE"),
    col("Average_Salary").alias("AVERAGE_SALARY"),
    col("REMOTE_GROUP"),
    col("LOT_V6_SPECIALIZED_OCCUPATION_NAME").alias("OCCUPATION_NAME")
)

df_pd = df_selected.toPandas()
df_pd.head()
```

	MAX_EXPERIENCE	AVERAGE_SALARY	REMOTE_GROUP	OCCUPATION_NAME
0	2.0	108668.5	Onsite	General ERP Analyst / Consultant
1	3.0	108668.5	Remote	Oracle Consultant / Analyst
2	7.0	108668.5	Onsite	General ERP Analyst / Consultant
3	2.0	92962.0	Onsite	Data Analyst
4	5.0	108668.5	Remote	Data Analyst

```

order      = ["Onsite", "Remote", "Hybrid"]
color_map = {"Onsite": "#2a9d8f", "Remote": "#e76f51", "Hybrid": "#264653"}

fig = px.scatter(
    df_pd,
    x="MAX_EXPERIENCE",
    y="AVERAGE_SALARY",
    color="REMOTE_GROUP",
    category_orders={"REMOTE_GROUP": order},
    color_discrete_map=color_map,
    title="Salary vs Experience by Remote Work Type",
    labels={
        "MAX_EXPERIENCE": "Years of Experience",
        "AVERAGE_SALARY": "Average Salary (USD)"
    },
    opacity=0.85,
    hover_data=["OCCUPATION_NAME", "MAX_EXPERIENCE", "AVERAGE_SALARY"]
)

fig.update_layout(
    paper_bgcolor="#F9FAFB",
    plot_bgcolor="#FFFFFF",
    margin=dict(l=60, r=60, t=80, b=70),
    xaxis=dict(
        tickmode="linear", dtick=1,
        gridcolor="rgba(0,0,0,0.1)",
        zeroline=False
    ),
    yaxis=dict(
        gridcolor="rgba(0,0,0,0.1)",
        zeroline=False
    )
)

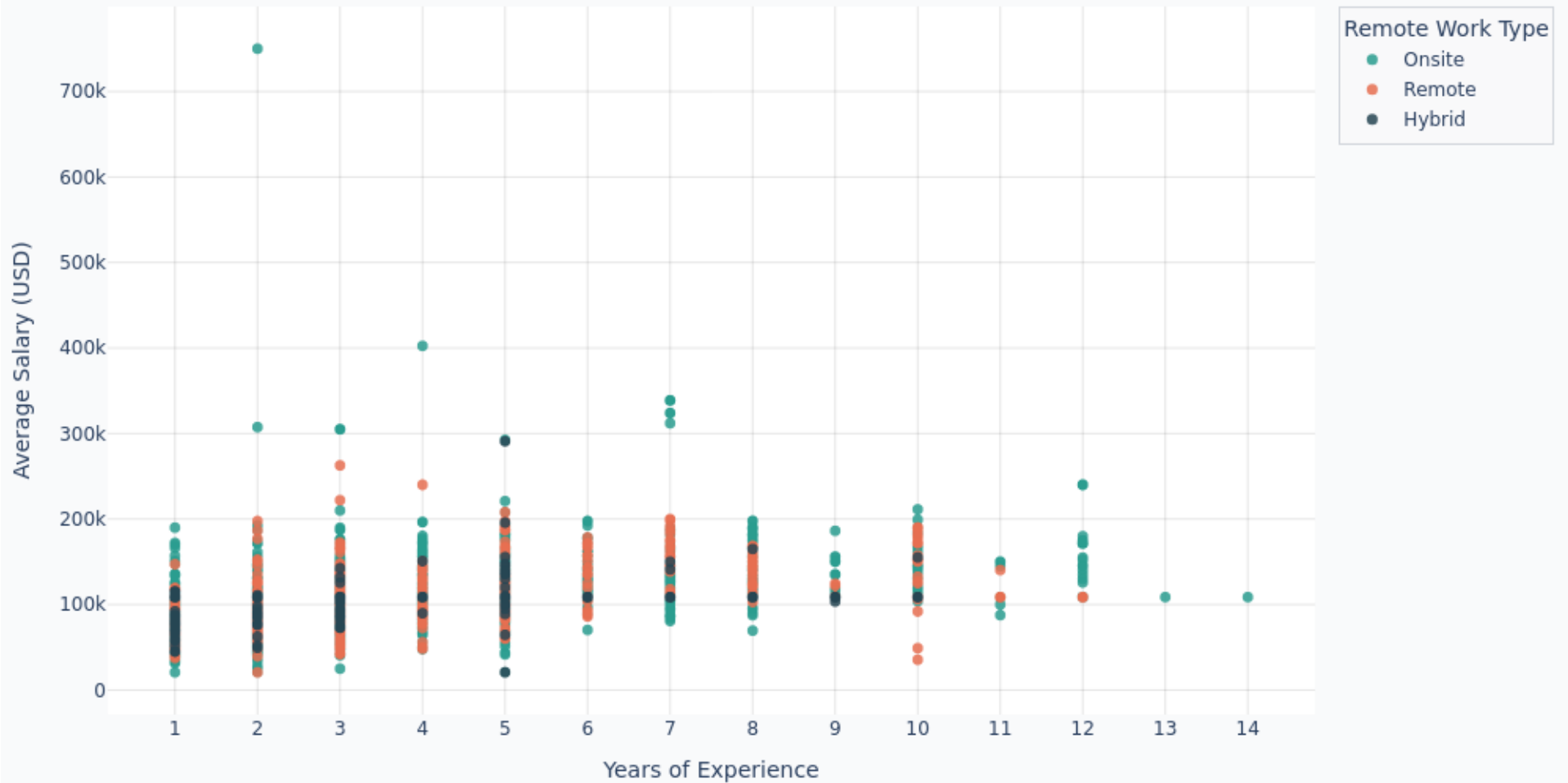
```

```
),
legend=dict(
    bgcolor="rgba(249,250,251,0.85)",
    bordercolor="#D1D5DB", borderwidth=1,
    title_text="Remote Work Type"
),
font_family="Arial",
title_font_size=18
)

fig.update_traces(marker=dict(size=7, opacity=0.85, line=dict(width=0)))

fig.write_html("./output/Q5.html")
fig.write_image("./output/Q5.png", width=1000, height=600, scale=1)
```

## Salary vs Experience by Remote Work Type



### 6.1 Interpretation

- Professionals across all work types (Onsite, Remote, Hybrid) demonstrate similar salary trends with increasing experience.
- Hybrid roles appear less frequent but generally align with the salary range of Onsite and Remote roles.