Assignment 03

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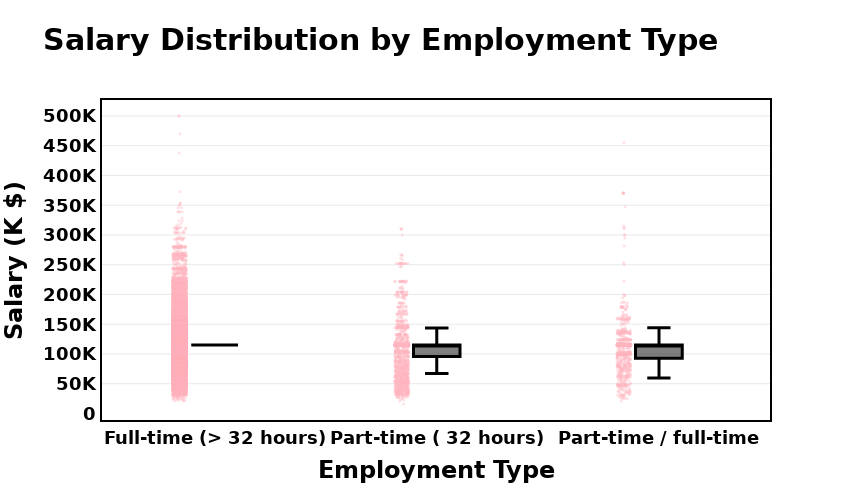
# 1. Load the Dataset

import os, sys  
os.environ["PYSPARK\_PYTHON"] = sys.executable  
os.environ["PYSPARK\_DRIVER\_PYTHON"] = sys.executable  
os.environ.pop("SPARK\_HOME", None)  
os.environ.pop("SPARK\_DIST\_CLASSPATH", None)  
os.makedirs("./output", exist\_ok=True)  
from pyspark.sql import SparkSession  
from pyspark.sql.functions import col, monotonically\_increasing\_id  
from pyspark.sql import functions as F  
import pandas as pd  
import numpy as np  
import plotly.io as pio  
from IPython.display import Image, display  
def show\_and\_save(fig, path, width=950, height=550, scale=2):  
 png\_bytes = fig.to\_image(format="png", width=width, height=height, scale=scale)  
 with open(path, "wb") as f:  
 f.write(png\_bytes)  
 display(Image(png\_bytes))   
np.random.seed(42)  
# Initialize Spark Session  
spark = SparkSession.builder.appName("LightcastData").getOrCreate()  
# Load Data  
df = spark.read.option("header", "true").option("inferSchema", "true").option("multiLine","true").option("escape", "\"").csv("./data/lightcast\_job\_postings.csv")  
df.createOrReplaceTempView("job\_postings")  
# Show Schema and Sample Data  
#print("---This is Diagnostic check, No need to print it in the final doc---")  
df.printSchema() # comment this line when rendering the submission  
#df.show(5)  
df = df.withColumn("SALARY", col("SALARY").cast("float")) \  
 .withColumn("MAX\_YEARS\_EXPERIENCE", col("MAX\_YEARS\_EXPERIENCE").cast("float"))  
  
def compute\_median(sdf, col\_name):  
 q = sdf.approxQuantile(col\_name, [0.5], 0.01)  
 return q[0] if q else None  
median\_salary = compute\_median(df, "SALARY")  
print("Median SALARY:", median\_salary)  
df = df.fillna({"SALARY": median\_salary})  
df = df.withColumn("Average\_Salary", col("SALARY"))  
export\_cols = [  
 "EDUCATION\_LEVELS\_NAME",  
 "REMOTE\_TYPE\_NAME",  
 "MAX\_YEARS\_EXPERIENCE",  
 "Average\_Salary",  
 "SALARY",  
 "LOT\_V6\_SPECIALIZED\_OCCUPATION\_NAME",  
 "EMPLOYMENT\_TYPE\_NAME"  
]  
df\_selected = df.select(\*export\_cols)  
pdf= df\_selected.toPandas()  
pdf.to\_csv("./output/cleaned\_subset.csv", index=False)  
print("Data Cleaning Complete. Rows Retained:", len(pdf))

root  
 |-- EDUCATION\_LEVELS\_NAME: string (nullable = true)  
 |-- REMOTE\_TYPE\_NAME: string (nullable = true)  
 |-- MAX\_YEARS\_EXPERIENCE: double (nullable = true)  
 |-- Average\_Salary: double (nullable = true)  
 |-- SALARY: double (nullable = true)  
 |-- LOT\_V6\_SPECIALIZED\_OCCUPATION\_NAME: string (nullable = true)  
 |-- EMPLOYMENT\_TYPE\_NAME: string (nullable = true)  
  
Median SALARY: 115024.0  
Data Cleaning Complete. Rows Retained: 72498

# 2. Salary Distribution by Employment Type

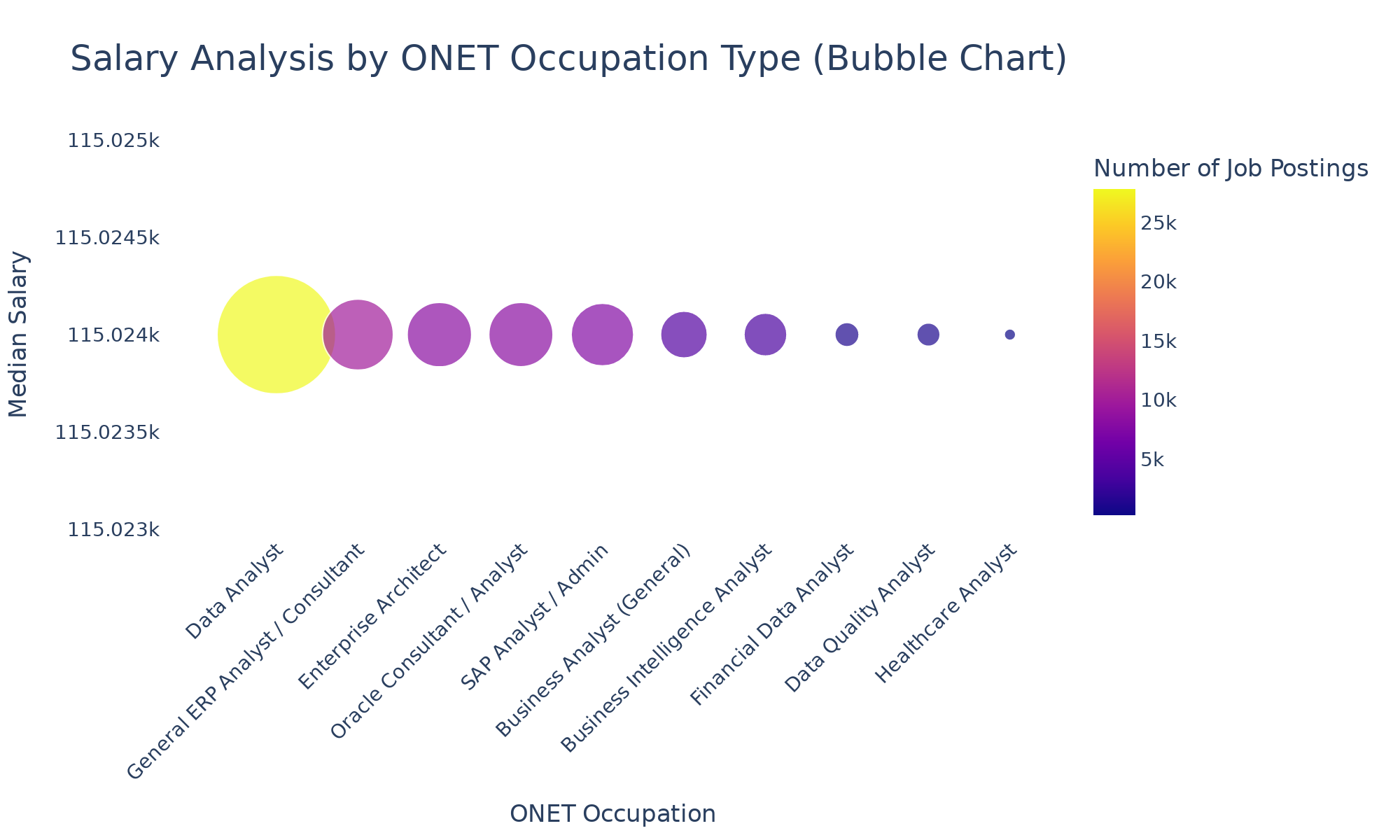
from pyspark.sql import SparkSession  
from pyspark.sql.functions import col  
import re  
import plotly.express as px  
import plotly.io as pio  
os.makedirs("output", exist\_ok=True)  
#Data Cleaning & Filtering  
pdf = df.filter(df["SALARY"] > 0).select("EMPLOYMENT\_TYPE\_NAME", "SALARY").toPandas()  
pdf["EMPLOYMENT\_TYPE\_NAME"] = pdf["EMPLOYMENT\_TYPE\_NAME"].apply(  
 lambda x: re.sub(r"[^\x00-\x7F]+", "", str(x)) if x is not None else x  
)  
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  
)  
#Creating the Boxplot  
fig = px.box(  
 pdf,  
 x="EMPLOYMENT\_TYPE\_NAME",  
 y="SALARY",  
 title="Salary Distribution by Employment Type",  
 color\_discrete\_sequence=["#ffb6c1", "#cb1a72ff", "#db7093", "#c71585"],  
 boxmode="group",  
 points="all"  
)  
fig.update\_traces(marker=dict(opacity=0.4, size=3),   
 line=dict(width=3, color="black"))  
fig.update\_layout(  
 title=dict(text="Salary Distribution by Employment Type", font=dict(size=30, family="Arial", color="black", weight="bold")),  
 margin=dict(t=100, b=80, l=80, r=80),  
 xaxis=dict(  
 title=dict(text="Employment Type", font=dict(size=24, family="Arial", color="black", weight="bold")),  
 tickangle=0,  
 tickfont=dict(size=18, family="Arial", color="black", weight="bold"),  
 showline=True, linewidth=2, linecolor="black", mirror=True,  
 showgrid=False,  
 categoryorder="array",  
 categoryarray=sorted\_employment\_types.tolist()  
 ),  
 yaxis=dict(  
 title=dict(text="Salary (K $)", font=dict(size=24, family="Arial", color="black", weight="bold")),  
 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=18, family="Arial", color="black", weight="bold"),  
 showline=True, linewidth=2, linecolor="black", mirror=True,  
 showgrid=True, gridcolor="lightgrey", gridwidth=0.5  
 ),  
 font=dict(family="Arial", size=16, color="black"),  
 boxgap=0.7,  
 plot\_bgcolor="white",  
 paper\_bgcolor="white",  
 showlegend=False,  
 height=500,  
 width=850  
)  
show\_and\_save(fig, "output/Q1.png", width=850, height=500, scale=1)



The box plot shows the salary distribution under different types of employment. From the graph, it can be seen that the sample size of “Full time (>32 hours)” is the largest, and the salary dispersion is also the highest, approaching $500000, indicating a wider range of job positions with salary distribution. In contrast, the sample size for “Part-time (32 hours)” is smaller, the distribution is more concentrated, and the overall level is lower; however, there are still a few high-paying outliers. And “Part-time/full-time” falls between the two, with an overall salary level higher than pure part-time but lower than full-time, and there are also a few high-salary outliers. Overall, full-time positions have the highest salary levels and the most significant fluctuations, while part-time positions are more concentrated and lower, and mixed types fall between the two.

# 3. Salary Analysis by ONET Occupation Type (Bubble Chart)

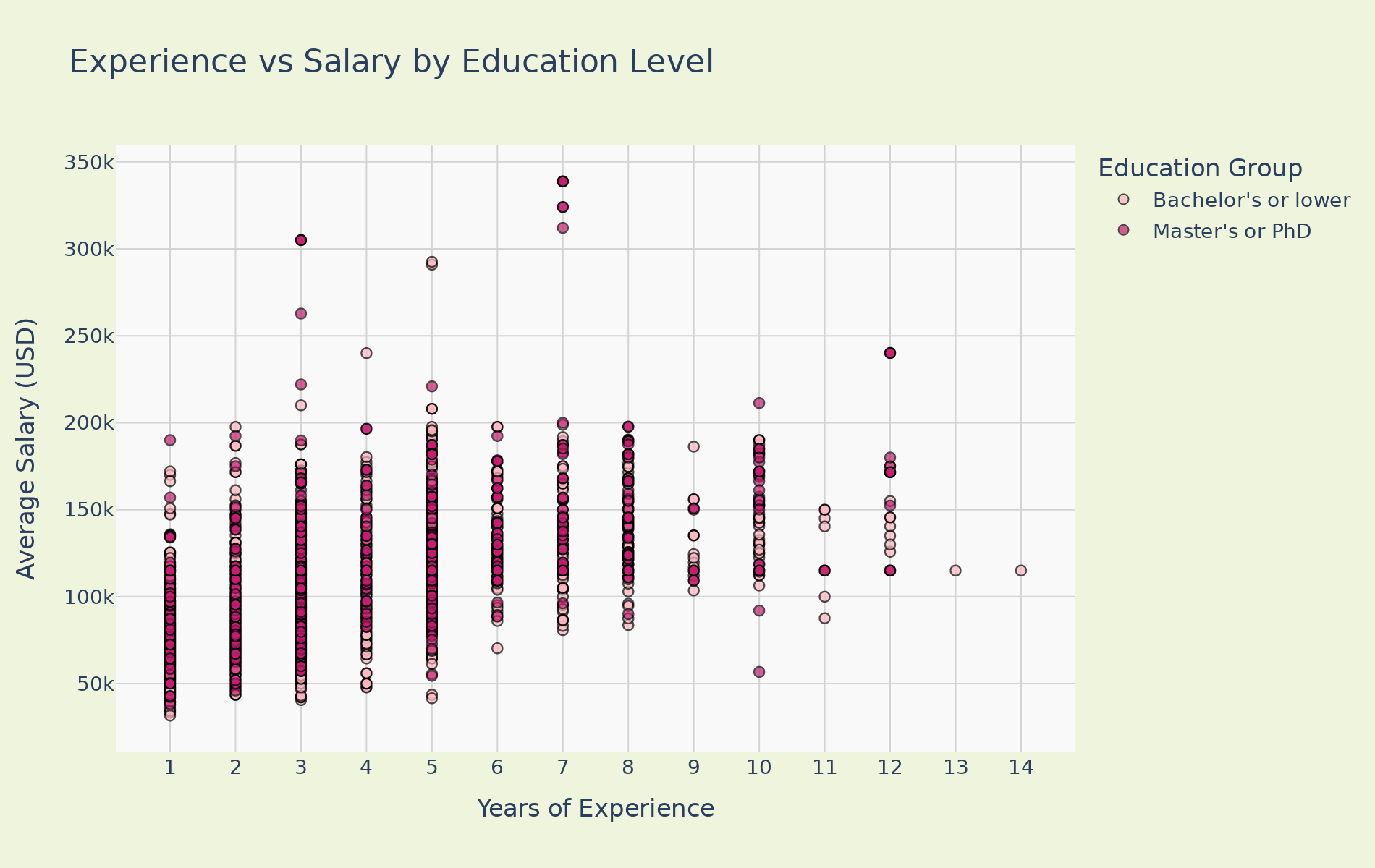
from pyspark.sql import SparkSession  
from pyspark.sql.functions import col  
import plotly.express as px  
os.makedirs("output", exist\_ok=True)  
#Spark SQL to Converting  
salary\_analysis = spark.sql("""  
 SELECT  
 LOT\_V6\_SPECIALIZED\_OCCUPATION\_NAME AS ONET\_NAME,  
 PERCENTILE(SALARY, 0.5) AS Median\_Salary,  
 COUNT(\*) AS Job\_Postings  
 FROM job\_postings  
 GROUP BY LOT\_V6\_SPECIALIZED\_OCCUPATION\_NAME  
 ORDER BY Job\_Postings DESC  
 LIMIT 10  
""")  
salary\_pd = salary\_analysis.toPandas()  
#Creating Bubble Chart  
fig = px.scatter(  
 salary\_pd,  
 x="ONET\_NAME",  
 y="Median\_Salary",  
 size="Job\_Postings",  
 title="Salary Analysis by ONET Occupation Type (Bubble Chart)",  
 labels={  
 "ONET\_NAME": "ONET Occupation",  
 "Median\_Salary": "Median Salary",  
 "Job\_Postings": "Number of Job Postings"  
 },  
 hover\_name="ONET\_NAME",  
 size\_max=60,  
 width=1000,  
 height=600,  
 color="Job\_Postings",  
 color\_discrete\_sequence=["#ffe4e1", "#ffb6c1", "#ff69b4", "#db7093", "#c71585"],  
)  
fig.update\_layout(  
 font\_family="Arial",  
 font\_size=14,  
 title\_font\_size=25,  
 xaxis\_title="ONET Occupation",  
 yaxis\_title="Median Salary",  
 plot\_bgcolor="white",  
 xaxis=dict(tickangle=-45, showline=True),  
 yaxis=dict(showline=True),  
 margin=dict(t=100, b=80, l=80, r=80)  
)  
show\_and\_save(fig, "output/Q2.png", width=1000, height=600, scale=2)



The bubble chart is based on SparkSQL to calculate the “Median Salary” and “Job Postings” for each ONET profession, and displays the top ten based on recruitment volume. The results show that Data Analyst has the largest bubble, ranking first, followed by General ERP Analyst/Consultant、Enterprise Architect、Oracle Consultant/Analyst The demand for data quality analysts and healthcare analysts is relatively small. It is worth noting that the median salary of the top ten professions is almost at the same level (about 115k), and the salary difference between professions is much smaller than the difference in recruitment volume, indicating that the market lacks clear differentiation in salary for different positions, and the greater difference is reflected in the scale of job demand.

# 4. Salary by Education Level

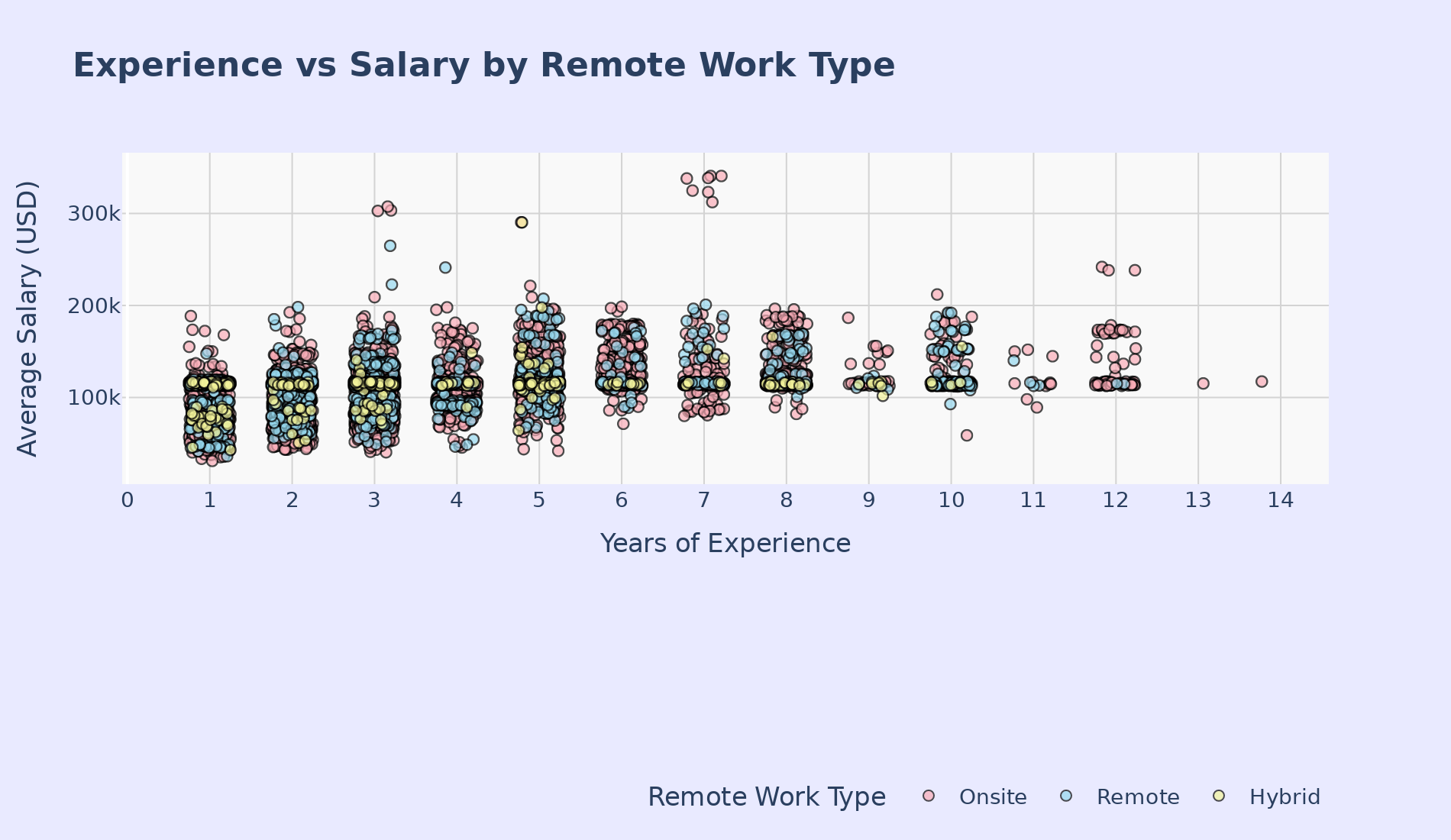
from pyspark.sql import SparkSession  
from pyspark.sql.functions import col, when, lit, trim, lower, regexp\_replace  
import plotly.express as px  
import plotly.io as pio  
os.makedirs("output", exist\_ok=True)  
#Building Educational Level Groups  
df = df.withColumn("EDU\_CLEAN", lower(trim(col("EDUCATION\_LEVELS\_NAME"))))  
df = df.withColumn(  
 "EDU\_GROUP",  
 when(col("EDU\_CLEAN").rlike("master|mba|msc"), lit("Master's or PhD"))  
 .when(col("EDU\_CLEAN").rlike("phd|doctor|professional"), lit("Master's or PhD"))  
 .when(col("EDU\_CLEAN").rlike("bachelor|associate|ged|high\\s\*school|no\\s\*education"), lit("Bachelor's or lower"))  
 .otherwise(lit("Other"))  
)  
df = df.withColumn("MAX\_YEARS\_EXPERIENCE", col("MAX\_YEARS\_EXPERIENCE").cast("double"))  
df = df.withColumn("Average\_Salary",  
 regexp\_replace(col("Average\_Salary"), "[$,]", "").cast("double"))  
df\_filtered = (  
 df.filter((col("MAX\_YEARS\_EXPERIENCE") > 0) & (col("Average\_Salary") > 0))  
 .filter(col("EDU\_GROUP").isin("Bachelor's or lower", "Master's or PhD"))  
 .select("MAX\_YEARS\_EXPERIENCE","Average\_Salary","EDU\_GROUP","LOT\_V6\_SPECIALIZED\_OCCUPATION\_NAME")  
)  
df\_pd = df\_filtered.toPandas()  
  
#Creating the Scatter Plot  
fig1 = px.scatter(  
 df\_pd,  
 x="MAX\_YEARS\_EXPERIENCE",  
 y="Average\_Salary",  
 color="EDU\_GROUP",  
 hover\_data=["LOT\_V6\_SPECIALIZED\_OCCUPATION\_NAME"],  
 opacity=0.7,  
 color\_discrete\_sequence=["#ffb6c1", "#cb1a72"],   
 title="Experience vs Salary by Education Level"  
)  
fig1.update\_traces(marker=dict(size=7, line=dict(width=1, color="black")))  
fig1.update\_layout(  
 plot\_bgcolor="#f9f9f9", paper\_bgcolor="#EFF5DC",  
 font=dict(family="Segoe UI", size=14),  
 title\_font=dict(size=22),  
 xaxis\_title="Years of Experience",  
 yaxis\_title="Average Salary (USD)",  
 legend\_title="Education Group",  
 hoverlabel=dict(bgcolor="white", font\_size=13, font\_family="Arial"),  
 xaxis=dict(gridcolor="lightgrey", tickmode="linear", dtick=1),  
 yaxis=dict(gridcolor="lightgrey"),  
 margin=dict(t=100, b=80, l=80, r=80)  
)  
show\_and\_save(fig1, "output/Q3.png", width=950, height=600, scale=2)



The scatter plot illustrates the relationship between work experience and average salary for different educational groups. Overall, with the increase of work experience, the salaries of both educational groups show a certain upward trend, but the distribution is relatively scattered. For the “Master’s or PhD” group, their average salary is generally higher than that of the “Bachelor’s or Lower” group, and their advantage is more obvious. At the same time, it can be seen that the high educated population appears more frequently in the high salary range of over $200000, while the low educated population is mostly concentrated in the middle and low salary range, which is between $50000 and $150000. It can be seen that higher education not only brings higher starting salaries in career development, but may also further widen the income gap after accumulating experience.

# 5. Salary by Remote Work Type

from pyspark.sql import SparkSession  
from pyspark.sql.functions import col  
from pyspark.sql.functions import when, trim  
import numpy as np  
import plotly.express as px  
import plotly.io as pio  
os.makedirs("output", exist\_ok=True)  
np.random.seed(42)  
  
#Work Types Data Setting  
df = df.withColumn("REMOTE\_GROUP",  
 when(trim(col("REMOTE\_TYPE\_NAME")) == "Remote", "Remote")  
 .when(trim(col("REMOTE\_TYPE\_NAME")) == "Hybrid Remote", "Hybrid")  
 .when(trim(col("REMOTE\_TYPE\_NAME")) == "Not Remote", "Onsite")  
 .when(col("REMOTE\_TYPE\_NAME").isNull(), "Onsite")  
 .otherwise("Onsite")  
)  
df = df.filter(  
 (col("MAX\_YEARS\_EXPERIENCE").isNotNull()) &  
 (col("Average\_Salary").isNotNull()) &  
 (col("MAX\_YEARS\_EXPERIENCE") > 0) &  
 (col("Average\_Salary") > 0)  
)  
df\_pd = df.select(  
 "MAX\_YEARS\_EXPERIENCE",   
 "Average\_Salary",   
 "LOT\_V6\_SPECIALIZED\_OCCUPATION\_NAME",   
 "REMOTE\_GROUP"  
).toPandas()  
#Mathematical Adjusting  
df\_pd["MAX\_EXPERIENCE\_JITTER"] = df\_pd["MAX\_YEARS\_EXPERIENCE"] + np.random.uniform(-0.25, 0.25, size=len(df\_pd))  
df\_pd["AVERAGE\_SALARY\_JITTER"] = df\_pd["Average\_Salary"] + np.random.uniform(-2500, 2500, size=len(df\_pd))  
df\_pd = df\_pd.round(2)  
df\_pd.head()  
df\_pd = df\_pd[df\_pd["AVERAGE\_SALARY\_JITTER"] <= 390000]  
  
#Creating the Scatter Plot  
fig1 = px.scatter(  
 df\_pd,  
 x="MAX\_EXPERIENCE\_JITTER",  
 y="AVERAGE\_SALARY\_JITTER",  
 color="REMOTE\_GROUP",  
 hover\_data=["LOT\_V6\_SPECIALIZED\_OCCUPATION\_NAME"],  
 title="<b>Experience vs Salary by Remote Work Type</b>",  
 opacity=0.7,  
 color\_discrete\_sequence=["#f9acb7", "#96d8ee", "#f3f39a"]   
)  
  
fig1.update\_traces(marker=dict(size=7, line=dict(width=1, color="black")))  
  
fig1.update\_layout(  
 plot\_bgcolor="#f9f9f9",  
 paper\_bgcolor="#E9EAFF",  
 font=dict(family="Segoe UI", size=14),  
 title\_font=dict(size=22),  
 margin=dict(t=100, b=80, l=80, r=80),  
 xaxis\_title="Years of Experience",  
 yaxis\_title="Average Salary (USD)",  
 legend\_title="Remote Work Type",  
 hoverlabel=dict(bgcolor="white", font\_size=13, font\_family="Arial"),  
 xaxis=dict(  
 gridcolor="lightgrey",  
 tickmode="linear",  
 tick0=1,  
 dtick=1,  
 tickangle=0  
 ),  
 yaxis=dict(gridcolor="lightgrey"),  
 legend=dict(orientation="h", yanchor="bottom", y=-1.02, xanchor="right", x=1)  
)  
  
show\_and\_save(fig1, "output/Q4.png", width=950, height=550, scale=2)



The scatter plot shows the relationship between work experience and average salary for different types of remote work. Overall, the salary distribution of Onsite (pink), Remote (light blue), and Hybrid (light yellow) highly overlaps in most experience ranges, indicating that remote attributes are not the core factor determining salary levels. Among them, Onsite has the largest number of positions and the widest coverage, while Remote and Hybrid have relatively fewer positions. However, in some experience periods, such as 3 and 7 years, higher salary points have emerged. With the increase of work experience, the salaries of the three types of work modes have an overall upward trend, but the differences are limited.