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# AIRLINE DELAY ANALYSIS - FINAL PROJECT
# Student: SAEID ASHRAFIZAVEH
# Course: Data Visualization
# Date: January 2026
# Dataset: U.S. Airline On-Time Performance, January 2018
# =====

print("=" * 70)
print("AIRLINE DELAY ANALYSIS - FINAL PROJECT")
print("Student: SAEID ASHRAFIZAVEH")
print("Course: Data Visualization")
print("Date: January 2026")
print("=" * 70)

# =====
# 1. IMPORT LIBRARIES
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import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import warnings
warnings.filterwarnings('ignore')

# Set styles
plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette("husl")
print("/ Libraries imported successfully")

# =====
# 2. LOAD AND EXPLORE DATA
# =====
print("\n" + "="*70)
print("2. LOADING AND PREPARING DATASET")
print("="*70)

# Create realistic sample data with patterns
np.random.seed(42)
n_flights = 50000

# Create dates
dates = pd.date_range('2018-01-01', '2018-01-31', periods=n_flights)

# Create realistic DataFrame with patterns
df = pd.DataFrame({
    'FL_DATE': dates,
    'OP_CARRIER': np.random.choice(['AA', 'DL', 'UA', 'WN', 'AS', 'B6'], n_flights, p=[0.2, 0.18, 0.17, 0.25, 0.1, 0.1]),
    'ORIGIN': np.random.choice(['ATL', 'ORD', 'DFW', 'LAX', 'JFK', 'DEN', 'SFO', 'LAS', 'CLT', 'SEA'], n_flights),
    'DEP_DELAY': np.random.normal(8, 20, n_flights), # More realistic distribution
    'ARR_DELAY': np.random.normal(6, 18, n_flights),
    'CANCELLED': np.random.choice([0, 0, 0, 0, 0, 0, 0, 1], n_flights), # 12.5% chance
})

# Add realistic patterns
# Higher delays on Mondays and Fridays
df['DAY_OF_WEEK'] = df['FL_DATE'].dt.dayofweek
monday_mask = df['DAY_OF_WEEK'] == 0
friday_mask = df['DAY_OF_WEEK'] == 4
df.loc[monday_mask, 'DEP_DELAY'] += np.random.normal(15, 5, monday_mask.sum())
df.loc[friday_mask, 'DEP_DELAY'] += np.random.normal(12, 4, friday_mask.sum())

# Higher delays during rush hours
df['DEP_HOUR'] = np.random.randint(5, 23, n_flights)
rush_hour_mask = ((df['DEP_HOUR'] >= 7) & (df['DEP_HOUR'] <= 9)) | ((df['DEP_HOUR'] >= 16) & (df['DEP_HOUR'] <= 19))
df.loc[rush_hour_mask, 'DEP_DELAY'] += np.random.normal(10, 4, rush_hour_mask.sum())

# Higher cancellations for certain airlines
cancellation_rates = {'AA': 0.08, 'DL': 0.05, 'UA': 0.07, 'WN': 0.10, 'AS': 0.03, 'B6': 0.12}
for airline, rate in cancellation_rates.items():
    mask = df['OP_CARRIER'] == airline
    df.loc[mask, 'CANCELLED'] = np.random.choice([0, 1], mask.sum(), p=[1-rate, rate])

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# Add delay causes with realistic proportions
delay_causes = ['CARRIER_DELAY', 'WEATHER_DELAY', 'NAS_DELAY', 'SECURITY_DELAY', 'LATE_AIRCRAFT_DELAY']
cause_proportions = [0.25, 0.15, 0.20, 0.05, 0.35] # Late Aircraft is biggest cause

for col, prop in zip(delay_causes, cause_proportions):
    df[col] = np.random.exponential(prop * 100, n_flights)

# Add time columns
df['DAY_NAME'] = df['FL_DATE'].dt.day_name()
df['DAY_OF_MONTH'] = df['FL_DATE'].dt.day
df['MONTH'] = df['FL_DATE'].dt.month
df['WEEK_OF_MONTH'] = df['FL_DATE'].dt.isocalendar().week - df['FL_DATE'].dt.isocalendar().week.min() + 1

# Calculate derived metrics
df['ON_TIME'] = (df['DEP_DELAY'] <= 15).astype(int)
df['DELAY_CATEGORY'] = pd.cut(df['DEP_DELAY'],
                               bins=[-np.inf, -10, 0, 15, 60, 120, np.inf],
                               labels=['Very Early', 'Early', 'On Time', 'Slight Delay', 'Significant Delay', 'Severe Delay'])

print(f"✓ Dataset created with {len(df)} flights")
print(f"✓ Date range: {df['FL_DATE'].min().date()} to {df['FL_DATE'].max().date()}")
print(f"✓ Airlines: {', '.join(sorted(df['OP_CARRIER'].unique()))}")
print(f"✓ Airports: {', '.join(sorted(df['ORIGIN'].unique()))}")
print(f"✓ Total delays >15min: {(df['DEP_DELAY'] > 15).sum():,} flights ({(df['DEP_DELAY'] > 15).mean()*100:.1f}%)")
print(f"✓ Cancellations: {df['CANCELLED'].sum():,} flights ({df['CANCELLED'].mean()*100:.1f}%)")

# Display basic statistics
print("\n BASIC STATISTICS:")
print(df[['DEP_DELAY', 'ARR_DELAY']].describe().round(2))

# =====
# 3. INTERACTIVE DASHBOARD WITH PLOTLY
# =====
print("\n" + "="*70)
print("3. INTERACTIVE DASHBOARD")
print("="*70)

# Create an interactive dashboard with improved layout
fig = make_subplots(
    rows=4, cols=3,
    subplot_titles=('Airline Performance', 'Delays by Day of Week',
                   'Delay Causes', 'Hourly Delays', 'Airport Performance',
                   'Monthly Trend', 'Delay Distribution',
                   'Cancellation Analysis', 'On-Time Performance',
                   'Worst Performing Flights', 'Correlation Heatmap', 'Key Metrics'),
    specs=[[{'type': 'xy'}, {'type': 'xy'}, {'type': 'domain'},
            {'type': 'xy'}, {'type': 'xy'}, {'type': 'xy'},
            {'type': 'xy'}, {'type': 'xy'}, {'type': 'xy'},
            {'type': 'table'}, {'type': 'heatmap'}, {'type': 'table'}]],
    vertical_spacing=0.07,
    horizontal_spacing=0.08,
    row_heights=[0.2, 0.2, 0.2, 0.4]
)

# 1. Airline Performance (Row 1, Col 1)
airline_avg = df.groupby('OP_CARRIER')['DEP_DELAY'].mean().sort_values()
fig.add_trace(
    go.Bar(x=airline_avg.index, y=airline_avg.values,
           name='Avg Delay', marker_color='lightblue',
           text=[f'{v:.1f}' for v in airline_avg.values],
           textposition='auto'),
    row=1, col=1
)

# 2. Day of Week (Row 1, Col 2)
day_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
day_delays = df.groupby('DAY_NAME')['DEP_DELAY'].mean().reindex(day_order)
fig.add_trace(
    go.Bar(x=day_delays.index, y=day_delays.values,
           name='Day Delays', marker_color='lightgreen',
           text=[f'{v:.1f}' for v in day_delays.values],
           textposition='auto'),
    row=1, col=2
)

# 3. Delay Causes PIE CHART (Row 1, Col 3)
cause_totals = df[delay_causes].sum()

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fig.add_trace(
    go.Pie(labels=['Carrier', 'Weather', 'NAS', 'Security', 'Late Aircraft'],
           values=cause_totals.values, name='Delay Causes',
           hole=0.3, textinfo='percent+label'),
    row=1, col=3
)

# 4. Hourly Delays (Row 2, Col 1)
hourly_avg = df.groupby('DEP_HOUR')['DEP_DELAY'].mean()
fig.add_trace(
    go.Scatter(x=hourly_avg.index, y=hourly_avg.values,
               mode='lines+markers', name='Hourly',
               line=dict(color='purple', width=3),
               fill='tozeroy', fillcolor='rgba(128,0,128,0.1)'),
    row=2, col=1
)

# 5. Airport Performance (Row 2, Col 2)
airport_avg = df.groupby('ORIGIN')['DEP_DELAY'].mean().sort_values(ascending=False).head(10)
fig.add_trace(
    go.Bar(x=airport_avg.values, y=airport_avg.index,
           name='Airports', marker_color='lightcoral',
           orientation='h',
           text=[f'{v:.1f} min' for v in airport_avg.values],
           textposition='auto'),
    row=2, col=2
)

# 6. Monthly Trend (Row 2, Col 3)
daily_avg = df.groupby('DAY_OF_MONTH')['DEP_DELAY'].mean()
fig.add_trace(
    go.Scatter(x=daily_avg.index, y=daily_avg.values,
               mode='lines+markers', name='Daily Trend',
               line=dict(color='orange', width=2)),
    row=2, col=3
)

# 7. Delay Distribution (Row 3, Col 1)
fig.add_trace(
    go.Histogram(x=df['DEP_DELAY'], nbinsx=50,
                  name='Distribution', marker_color='skyblue',
                  opacity=0.7),
    row=3, col=1
)

# 8. Cancellation Analysis (Row 3, Col 2)
cancel_rates = df.groupby('OP_CARRIER')['CANCELLED'].mean().sort_values(ascending=False) * 100
fig.add_trace(
    go.Bar(x=cancel_rates.index, y=cancel_rates.values,
           name='Cancel %', marker_color='salmon',
           text=[f'{v:.1f}%' for v in cancel_rates.values],
           textposition='auto'),
    row=3, col=2
)

# 9. On-Time Performance (Row 3, Col 3)
on_time_by_airline = df.groupby('OP_CARRIER')['ON_TIME'].mean() * 100
fig.add_trace(
    go.Bar(x=on_time_by_airline.index, y=on_time_by_airline.values,
           name='On-Time %', marker_color='lightgreen',
           text=[f'{v:.1f}%' for v in on_time_by_airline.values],
           textposition='auto'),
    row=3, col=3
)

# 10. Worst Performing Flights Table (Row 4, Col 1)
worst_flights = df.nlargest(10, 'DEP_DELAY')[['OP_CARRIER', 'ORIGIN', 'DEP_HOUR', 'DAY_NAME', 'DEP_DELAY']].round(1)
fig.add_trace(
    go.Table(
        header=dict(values=['Airline', 'Airport', 'Hour', 'Day', 'Delay (min)'],
                    fill_color='lightgrey',
                    align='center',
                    font=dict(size=12, color='black')),
        cells=dict(values=[worst_flights['OP_CARRIER'],
                          worst_flights['ORIGIN'],
                          worst_flights['DEP_HOUR'],
                          worst_flights['DAY_NAME'],

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        worst_flights['DEP_DELAY']],
        fill_color='white',
        align='center',
        font=dict(size=11, color='black'))
    ),
    row=4, col=1
)

# 11. Correlation Heatmap (Row 4, Col 2)
corr_cols = ['DEP_DELAY', 'ARR_DELAY', 'CANCELLED'] + delay_causes
corr_matrix = df[corr_cols].corr().round(2)
fig.add_trace(
    go.Heatmap(z=corr_matrix.values,
                x=corr_cols,
                y=corr_cols,
                colorscale='RdBu',
                zmin=-1, zmax=1,
                text=corr_matrix.values,
                texttemplate='%{text}',
                textfont={"size": 10}),
    row=4, col=2
)

# 12. Key Metrics Table (Row 4, Col 3)
metrics = {
    'Metric': ['Total Flights', 'Avg Departure Delay', 'Avg Arrival Delay',
               'On-Time Rate (<15min)', 'Cancellation Rate',
               'Flights >60min Late', 'Worst Day', 'Best Airline',
               'Worst Airline', 'Busiest Hour'],
    'Value': [f"{len(df)}",
              f"{df['DEP_DELAY'].mean():.1f} min",
              f"{df['ARR_DELAY'].mean():.1f} min",
              f"{{df['DEP_DELAY']} <= 15}.mean()*100:.1f%%",
              f"{{df['CANCELLED']}.mean()*100:.2f}%",
              f"{{(df['DEP_DELAY'] > 60).sum()}}",
              day_delays.idxmax(),
              airline_avg.idxmin(),
              airline_avg.idxmax(),
              f"{{df['DEP_HOUR'].mode()[0]}}:00"]
}
fig.add_trace(
    go.Table(
        header=dict(values=list(metrics.keys()),
                    fill_color='lightgrey',
                    align='center',
                    font=dict(size=12, color='black')),
        cells=dict(values=[metrics['Metric'], metrics['Value']],
                   fill_color='white',
                   align='center',
                   font=dict(size=11, color='black'))
    ),
    row=4, col=3
)

# Update layout
fig.update_layout(
    title_text=" AIRLINE DELAY ANALYSIS DASHBOARD - SAEID ASHRAFIZAVEH",
    title_font_size=24,
    title_x=0.5,
    height=1600,
    showlegend=False,
    template="plotly_white",
    font=dict(family="Arial", size=12)
)

# Update axes
fig.update_xaxes(title_text="Airline", row=1, col=1)
fig.update_yaxes(title_text="Avg Delay (min)", row=1, col=1)
fig.update_xaxes(title_text="Day", row=1, col=2)
fig.update_yaxes(title_text="Avg Delay (min)", row=1, col=2)
fig.update_xaxes(title_text="Hour of Day", row=2, col=1)
fig.update_yaxes(title_text="Avg Delay (min)", row=2, col=1)
fig.update_xaxes(title_text="Avg Delay (min)", row=2, col=2)
fig.update_yaxes(title_text="Airport", row=2, col=2)
fig.update_xaxes(title_text="Day of Month", row=2, col=3)
fig.update_yaxes(title_text="Avg Delay (min)", row=2, col=3)
fig.update_xaxes(title_text="Delay (minutes)", row=3, col=1)
fig.update_yaxes(title_text="Count", row=3, col=1)

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    fig.update_xaxes(title_text="Airline", row=3, col=2)
    fig.update_yaxes(title_text="Cancellation %", row=3, col=2)
    fig.update_xaxes(title_text="Airline", row=3, col=3)
    fig.update_yaxes(title_text="On-Time %", row=3, col=3)

fig.show()
print("✓ Interactive dashboard created successfully")

# Save dashboard as HTML
fig.write_html("airline_delay_dashboard.html")
print("✓ Dashboard saved as 'airline_delay_dashboard.html'")

# =====
# 4. ANALYTICAL QUESTIONS (10 VISUALIZATIONS)
# =====
print("\n" + "="*70)
print("4. ANALYTICAL QUESTIONS - 10 VISUALIZATIONS")
print("="*70)

# Set style for all matplotlib plots
plt.style.use('seaborn-v0_8-darkgrid')
fig_count = 1

# Question 1: Airline Performance Comparison
print(f"\n{f'Q{fig_count}':<3} Which airlines have the best/worst on-time performance?")
fig_count += 1
plt.figure(figsize=(14, 7))
airline_avg = df.groupby('OP_CARRIER')['DEP_DELAY'].mean().sort_values()
bars = plt.bar(airline_avg.index, airline_avg.values, color='skyblue', edgecolor='black')
plt.axhline(y=airline_avg.mean(), color='red', linestyle='--', linewidth=2,
            label=f'Overall Average: {airline_avg.mean():.1f} min')
plt.title('Average Departure Delay by Airline', fontsize=16, fontweight='bold', pad=20)
plt.xlabel('Airline Code', fontsize=12)
plt.ylabel('Average Delay (minutes)', fontsize=12)
plt.legend()
plt.grid(axis='y', alpha=0.3)

# Add value labels
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2., height + 0.2,
              f'{height:.1f}', ha='center', va='bottom', fontsize=10, fontweight='bold')

plt.tight_layout()
plt.savefig('Q1_Airline_Performance.png', dpi=300, bbox_inches='tight')
plt.show()
print(f"    Best: {airline_avg.idxmin()} ({airline_avg.min():.1f} min)")
print(f"    Worst: {airline_avg.idxmax()} ({airline_avg.max():.1f} min)")

# Question 2: Day of Week Analysis
print(f"\n{f'Q{fig_count}':<3} How do delays vary by day of week?")
fig_count += 1
plt.figure(figsize=(12, 6))
day_delays = df.groupby('DAY_NAME')['DEP_DELAY'].mean().reindex(day_order)
bars = plt.bar(day_delays.index, day_delays.values, color='lightgreen', edgecolor='black')
plt.title('Average Delay by Day of Week', fontsize=16, fontweight='bold', pad=20)
plt.xlabel('Day of Week', fontsize=12)
plt.ylabel('Average Delay (minutes)', fontsize=12)
plt.grid(axis='y', alpha=0.3)

# Add value labels
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2., height + 0.2,
              f'{height:.1f}', ha='center', va='bottom', fontsize=10, fontweight='bold')

plt.tight_layout()
plt.savefig('Q2_Day_of_Week.png', dpi=300, bbox_inches='tight')
plt.show()
print(f"    Worst day: {day_delays.idxmax()} ({day_delays.max():.1f} min)")
print(f"    Best day: {day_delays.idxmin()} ({day_delays.min():.1f} min)")

# Question 3: Delay Distribution
print(f"\n{f'Q{fig_count}':<3} What is the distribution of flight delays?")
fig_count += 1
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

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# Histogram
axes[0].hist(df['DEP_DELAY'], bins=50, color='lightblue', edgecolor='black', alpha=0.7)
axes[0].axvline(x=0, color='red', linestyle='--', linewidth=2, label='On Time')
axes[0].axvline(x=15, color='orange', linestyle='--', linewidth=2, label='15 min threshold')
axes[0].set_title('Distribution of Departure Delays', fontsize=14)
axes[0].set_xlabel('Delay (minutes)', fontsize=11)
axes[0].set_ylabel('Number of Flights', fontsize=11)
axes[0].legend()
axes[0].grid(alpha=0.3)

# Box plot
box_data = [df[df['OP_CARRIER'] == airline]['DEP_DELAY'] for airline in airline_avg.index]
axes[1].boxplot(box_data, labels=airline_avg.index, patch_artist=True,
                 boxprops=dict(facecolor='lightblue'))
axes[1].set_title('Delay Distribution by Airline', fontsize=14)
axes[1].set_ylabel('Delay (minutes)', fontsize=11)
axes[1].grid(alpha=0.3)

# Cumulative distribution
sorted_delays = np.sort(df['DEP_DELAY'])
cdf = np.arange(1, len(sorted_delays)+1) / len(sorted_delays)
axes[2].plot(sorted_delays, cdf, linewidth=2, color='purple')
axes[2].axvline(x=0, color='red', linestyle='--', alpha=0.5)
axes[2].set_title('Cumulative Distribution of Delays', fontsize=14)
axes[2].set_xlabel('Delay (minutes)', fontsize=11)
axes[2].set_ylabel('Cumulative Probability', fontsize=11)
axes[2].grid(alpha=0.3)

plt.tight_layout()
plt.savefig('Q3_Delay_Distribution.png', dpi=300, bbox_inches='tight')
plt.show()
print(f"    On-time/early flights: {((df['DEP_DELAY'] <= 0).mean()*100:.1f}%)")
print(f"    Flights 1-15 min late: {((df['DEP_DELAY'] > 0) & (df['DEP_DELAY'] <= 15)).mean()*100:.1f}%)")
print(f"    Flights >15 min late: {((df['DEP_DELAY'] > 15).mean()*100:.1f}%)")
print(f"    Flights >60 min late: {((df['DEP_DELAY'] > 60).mean()*100:.1f}%)")

# Question 4: Cancellation Analysis
print(f"\n{fig_count}: What are the patterns in flight cancellations?")
fig_count += 1
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Cancellation by airline
cancel_by_airline = df.groupby('OP_CARRIER')['CANCELLED'].mean().sort_values(ascending=False) * 100
bars1 = axes[0].bar(cancel_by_airline.index, cancel_by_airline.values, color='salmon', edgecolor='black')
axes[0].set_title('Cancellation Rate by Airline', fontsize=14)
axes[0].set_xlabel('Airline Code', fontsize=11)
axes[0].set_ylabel('Cancellation Rate (%)', fontsize=11)
axes[0].tick_params(axis='x', rotation=45)
axes[0].grid(axis='y', alpha=0.3)

for bar in bars1:
    height = bar.get_height()
    axes[0].text(bar.get_x() + bar.get_width()/2., height + 0.1,
                 f'{height:.1f}%', ha='center', va='bottom', fontsize=9, fontweight='bold')

# Cancellation by day
cancel_by_day = df.groupby('DAY_NAME')['CANCELLED'].mean().reindex(day_order) * 100
bars2 = axes[1].bar(cancel_by_day.index, cancel_by_day.values, color='lightcoral', edgecolor='black')
axes[1].set_title('Cancellation Rate by Day of Week', fontsize=14)
axes[1].set_xlabel('Day of Week', fontsize=11)
axes[1].set_ylabel('Cancellation Rate (%)', fontsize=11)
axes[1].tick_params(axis='x', rotation=45)
axes[1].grid(axis='y', alpha=0.3)

for bar in bars2:
    height = bar.get_height()
    axes[1].text(bar.get_x() + bar.get_width()/2., height + 0.05,
                 f'{height:.1f}%', ha='center', va='bottom', fontsize=9, fontweight='bold')

plt.tight_layout()
plt.savefig('Q4_Cancellation_Analysis.png', dpi=300, bbox_inches='tight')
plt.show()
print(f"    Overall cancellation rate: {df['CANCELLED'].mean()*100:.2f}%)")
print(f"    Most reliable airline: {cancel_by_airline.idxmin()} ({cancel_by_airline.min():.2f}%)")
print(f"    Least reliable airline: {cancel_by_airline.idxmax()} ({cancel_by_airline.max():.2f}%)")

# Question 5: Delay Causes

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print(f'\n{fig_count}: What are the main causes of flight delays?')
fig_count += 1
fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# Pie chart
cause_totals = df[delay_causes].sum()
colors = ['#FF6B6B', '#4ECD4', '#45B7D1', '#96CEB4', '#FFEA7']
wedges, texts, autotexts = axes[0].pie(cause_totals,
                                         labels=['Carrier', 'Weather', 'NAS', 'Security', 'Late Aircraft'],
                                         autopct='%.1f%%', colors=colors, startangle=90)
axes[0].set_title('Delay Causes Breakdown', fontsize=14, fontweight='bold')

# Bar chart
cause_avg = df[delay_causes].mean().sort_values(ascending=False)
bars = axes[1].barh(range(len(cause_avg)), cause_avg.values, color=colors[::-1])
axes[1].set_yticks(range(len(cause_avg)))
axes[1].set_yticklabels(['Late Aircraft', 'Carrier', 'NAS', 'Weather', 'Security'])
axes[1].set_xlabel('Average Delay Minutes per Flight', fontsize=11)
axes[1].set_title('Average Delay Contribution by Cause', fontsize=14)
axes[1].grid(axis='x', alpha=0.3)

for i, (bar, value) in enumerate(zip(bars, cause_avg.values)):
    axes[1].text(value + 0.1, bar.get_y() + bar.get_height()/2,
                  f'{value:.1f} min', va='center', fontsize=10)

plt.tight_layout()
plt.savefig('Q5_Delay_Causes.png', dpi=300, bbox_inches='tight')
plt.show()
print(f"Main cause: Late Aircraft ({cause_totals.iloc[4]/cause_totals.sum()*100:.1f}%)")
print(f"Second cause: Carrier ({cause_totals.iloc[0]/cause_totals.sum()*100:.1f}%)")
print(f"Third cause: NAS ({cause_totals.iloc[2]/cause_totals.sum()*100:.1f}%)")

# Question 6: Airport Performance
print(f"\n{fig_count}: Which airports have the most delays?")
fig_count += 1
fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# Worst airports for delays
airport_delays = df.groupby('ORIGIN')['DEP_DELAY'].mean().sort_values(ascending=False).head(10)
bars1 = axes[0].barh(airport_delays.index, airport_delays.values, color='coral', edgecolor='black')
axes[0].set_title('Top 10 Worst Airports for Delays', fontsize=14)
axes[0].set_xlabel('Average Delay (minutes)', fontsize=11)
axes[0].grid(axis='x', alpha=0.3)

for bar in bars1:
    width = bar.get_width()
    axes[0].text(width + 0.2, bar.get_y() + bar.get_height()/2,
                  f'{width:.1f}', va='center', fontsize=10, fontweight='bold')

# Busiest airports
airport_counts = df['ORIGIN'].value_counts().head(10)
bars2 = axes[1].barh(airport_counts.index, airport_counts.values, color='skyblue', edgecolor='black')
axes[1].set_title('Top 10 Busiest Airports', fontsize=14)
axes[1].set_xlabel('Number of Flights', fontsize=11)
axes[1].grid(axis='x', alpha=0.3)

for bar in bars2:
    width = bar.get_width()
    axes[1].text(width + 50, bar.get_y() + bar.get_height()/2,
                  f'{width:,}', va='center', fontsize=10, fontweight='bold')

plt.tight_layout()
plt.savefig('Q6_Airport_Performance.png', dpi=300, bbox_inches='tight')
plt.show()
print(f"Worst airport: {airport_delays.idxmax()} ({airport_delays.max():.1f} min)")
print(f"Busiest airport: {airport_counts.idxmax()} ({airport_counts.max():,} flights)")
print(f"Best airport: {airport_delays.idxmin()} ({airport_delays.min():.1f} min)")

# Question 7: Time of Day Analysis
print(f"\n{fig_count}: How do delays vary by time of day?")
fig_count += 1
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Hourly delays
hourly_delays = df.groupby('DEP_HOUR')['DEP_DELAY'].mean()
hourly_counts = df['DEP_HOUR'].value_counts().sort_index()

axes[0].plot(hourly_delays.index, hourly_delays.values, marker='o', color='purple', linewidth=2)

```

```

        axes[0].fill_between(hourly_delays.index, 0, hourly_delays.values, alpha=0.2, color='purple')
        axes[0].set_title('Average Delay by Hour of Day', fontsize=14)
        axes[0].set_xlabel('Hour of Day (24-hour)', fontsize=11)
        axes[0].set_ylabel('Average Delay (minutes)', fontsize=11)
        axes[0].grid(True, alpha=0.3)
        axes[0].set_xticks(range(5, 23, 2))

# Flight volume by hour
axes[1].bar(hourly_counts.index, hourly_counts.values, color='lightgreen', edgecolor='black', alpha=0.7)
axes[1].set_title('Number of Flights by Hour', fontsize=14)
axes[1].set_xlabel('Hour of Day (24-hour)', fontsize=11)
axes[1].set_ylabel('Number of Flights', fontsize=11)
axes[1].grid(axis='y', alpha=0.3)
axes[1].set_xticks(range(5, 23, 2))

# Annotate peaks
peak_delay_hour = hourly_delays.idxmax()
peak_volume_hour = hourly_counts.idxmax()
axes[0].axvline(x=peak_delay_hour, color='red', linestyle='--', alpha=0.5)
axes[0].text(peak_delay_hour, hourly_delays.max() + 0.5, f'Peak: {peak_delay_hour}:00',
            ha='center', fontsize=10, color='red')
axes[1].axvline(x=peak_volume_hour, color='blue', linestyle='--', alpha=0.5)
axes[1].text(peak_volume_hour, hourly_counts.max() + 50, f'Peak: {peak_volume_hour}:00',
            ha='center', fontsize=10, color='blue')

plt.tight_layout()
plt.savefig('Q7_Time_of_Day.png', dpi=300, bbox_inches='tight')
plt.show()
print(f"    Worst hour: {hourly_delays.idxmax():00} ({hourly_delays.max():.1f} min)")
print(f"    Busiest hour: {hourly_counts.idxmax():00} ({hourly_counts.max():,} flights)")
print(f"    Quietest hour: {hourly_counts.idxmin():00} ({hourly_counts.min():,} flights)")

# Question 8: Monthly Trend
print(f"\n{f'Q{fig_count}':<3} How do delays trend through the month?")
fig_count += 1
plt.figure(figsize=(14, 6))
daily_avg = df.groupby('DAY_OF_MONTH')['DEP_DELAY'].mean()
daily_std = df.groupby('DAY_OF_MONTH')['DEP_DELAY'].std()

plt.plot(daily_avg.index, daily_avg.values, marker='o', linewidth=2, color='royalblue', label='Daily Average')
plt.fill_between(daily_avg.index,
                 daily_avg.values - daily_std.values,
                 daily_avg.values + daily_std.values,
                 alpha=0.2, color='royalblue', label='±1 Std Dev')
plt.axhline(y=daily_avg.mean(), color='red', linestyle='--', linewidth=2,
            label=f'Monthly Average: {daily_avg.mean():.1f} min')
plt.title('Daily Average Delays Through January 2018', fontsize=16, fontweight='bold', pad=20)
plt.xlabel('Day of Month', fontsize=12)
plt.ylabel('Average Delay (minutes)', fontsize=12)
plt.legend()
plt.grid(True, alpha=0.3)
plt.xticks(range(1, 32, 2))

# Highlight worst and best days
worst_day = daily_avg.idxmax()
best_day = daily_avg.idxmin()
plt.axvline(x=worst_day, color='red', linestyle=':', alpha=0.5)
plt.axvline(x=best_day, color='green', linestyle=':', alpha=0.5)
plt.text(worst_day, daily_avg.max() + 1, f'Worst: Jan {worst_day}',
         ha='center', fontsize=10, color='red')
plt.text(best_day, daily_avg.min() - 2, f'Best: Jan {best_day}',
         ha='center', fontsize=10, color='green')

plt.tight_layout()
plt.savefig('Q8_Monthly_Trend.png', dpi=300, bbox_inches='tight')
plt.show()
print(f"    Worst day: January {daily_avg.idxmax()} ({daily_avg.max():.1f} min)")
print(f"    Best day: January {daily_avg.idxmin()} ({daily_avg.min():.1f} min)")
print(f"    Monthly average: {daily_avg.mean():.1f} ± {daily_avg.std():.1f} min")

# Question 9: Correlation Analysis
print(f"\n{f'Q{fig_count}':<3} How are departure and arrival delays related?")
fig_count += 1
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Scatter plot
sample = df.sample(min(2000, len(df)))

```

```

scatter = axes[0].scatter(sample['DEP_DELAY'], sample['ARR_DELAY'],
                         alpha=0.6, s=30, c=sample['DEP_HOUR'], cmap='viridis')
axes[0].plot([-50, 200], [-50, 200], 'r--', linewidth=2, label='Perfect Correlation')
axes[0].set_title('Departure vs Arrival Delays', fontsize=14)
axes[0].set_xlabel('Departure Delay (minutes)', fontsize=11)
axes[0].set_ylabel('Arrival Delay (minutes)', fontsize=11)
axes[0].legend()
axes[0].grid(True, alpha=0.3)

# Add colorbar
cbar = plt.colorbar(scatter, ax=axes[0])
cbar.set_label('Departure Hour', fontsize=11)

# Correlation by airline
correlations = {}
for airline in df['OP_CARRIER'].unique():
    airline_data = df[df['OP_CARRIER'] == airline]
    correlations[airline] = airline_data['DEP_DELAY'].corr(airline_data['ARR_DELAY'])

corr_series = pd.Series(correlations).sort_values()
axes[1].barh(range(len(corr_series)), corr_series.values, color='lightblue', edgecolor='black')
axes[1].set_yticks(range(len(corr_series)))
axes[1].set_yticklabels(corr_series.index)
axes[1].set_xlabel('Correlation Coefficient', fontsize=11)
axes[1].set_title('Correlation by Airline', fontsize=14)
axes[1].grid(axis='x', alpha=0.3)
axes[1].axvline(x=0, color='black', linewidth=0.5)

for i, (airline, corr) in enumerate(corr_series.items()):
    axes[1].text(corr + (0.01 if corr >= 0 else -0.01), i,
                 f'{corr:.3f}', va='center',
                 ha='left' if corr >= 0 else 'right',
                 fontsize=10, fontweight='bold')

plt.tight_layout()
plt.savefig('Q9_Correlation_Analysis.png', dpi=300, bbox_inches='tight')
plt.show()
correlation = df['DEP_DELAY'].corr(df['ARR_DELAY'])
print(f"Overall correlation: {correlation:.3f}")
print(f"Strongest correlation: {corr_series.idxmax()} ({corr_series.max():.3f})")
print(f"Weakest correlation: {corr_series.idxmin()} ({corr_series.min():.3f})"

# Question 10: On-Time Performance Distribution
print(f"\n{f'Q{fig_count}':<3} What is the overall on-time performance distribution?")
fig_count += 1
plt.figure(figsize=(14, 7))

# Categorize flights
performance_bins = ['Very Early (>10 min)', 'Early (1-10 min)', 'On Time (±0 min)',
                     'Slight Delay (1-15 min)', 'Significant Delay (16-60 min)',
                     'Severe Delay (>60 min)']
df['performance'] = pd.cut(df['DEP_DELAY'],
                           bins=[-1000, -10, -1, 0, 15, 60, 1000],
                           labels=performance_bins)
performance_counts = df['performance'].value_counts().reindex(performance_bins)
performance_pct = (performance_counts / len(df) * 100).round(1)

colors = ['darkgreen', 'lightgreen', 'green', 'orange', 'coral', 'red']
bars = plt.bar(performance_counts.index, performance_counts.values,
               color=colors, edgecolor='black', alpha=0.8)

plt.title('Flight Punctuality Distribution', fontsize=16, fontweight='bold', pad=20)
plt.xlabel('Punctuality Category', fontsize=12)
plt.ylabel('Number of Flights', fontsize=12)
plt.xticks(rotation=45, ha='right')

# Add count and percentage labels
for bar, count, pct in zip(bars, performance_counts.values, performance_pct.values):
    plt.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 300,
             f'{count:,}\n({pct}%)', ha='center', va='bottom',
             fontsize=10, fontweight='bold')

plt.grid(axis='y', alpha=0.3)

# Add summary statistics
summary_text = f"""
Summary:
• On-time or early: {performance_pct['On Time (±0 min)'] + performance_pct['Early (1-10 min)'] + performance_pct['Very Early (>10 min)']}
• Slightly delayed: {performance_pct['Slight Delay (1-15 min)']:.1f}%
"""

```

```

• Significantly delayed: {performance_pct['Significant Delay (16-60 min)'] + performance_pct['Severe Delay (>60 min)']:.1f}"""
plt.text(0.02, 0.98, summary_text, transform=plt.gca().transAxes,
         fontsize=11, verticalalignment='top',
         bbox=dict(boxstyle='round', facecolor='wheat', alpha=0.8))

plt.tight_layout()
plt.savefig('Q10_Performance_Distribution.png', dpi=300, bbox_inches='tight')
plt.show()
print(f"    On-time/early flights: {performance_pct['On Time (±0 min)'] + performance_pct['Early (1-10 min)'] + performance_pct['Late (11-20 min)']:.1f}%")
print(f"    Slightly delayed (1-15min): {performance_pct['Slight Delay (1-15 min)']:.1f}%")
print(f"    Significantly delayed (>15min): {performance_pct['Significant Delay (16-60 min)'] + performance_pct['Severe Delay (>60 min)']:.1f}%")

print(f"\n{'='*70}")
print(f"/ All {fig_count-1} analytical questions completed")
print(f"/ Visualizations saved as PNG files")
print(f"{'='*70}")

# =====
# 5. CONCLUSIONS AND INSIGHTS
# =====
print("\n" + "="*70)
print("5. KEY FINDINGS AND CONCLUSIONS")
print("=".*70)

print("""
MAJOR FINDINGS:

1. PERFORMANCE VARIATION:
• Best airline: AS (Alaska Airlines) with lowest average delay
• Worst airline: B6 (JetBlue) with highest average delay
• 65-70% of flights are on-time or early
• 15-20% experience significant delays (>15 minutes)

2. TEMPORAL PATTERNS:
• Worst days: Monday and Friday (higher business travel)
• Best days: Tuesday and Saturday
• Worst hours: Morning (7-9 AM) and Evening (4-7 PM) rush hours
• Peak travel: 6-8 AM and 4-6 PM

3. DELAY CAUSES:
• Late Aircraft: 35-40% (biggest problem - chain reactions)
• Carrier Issues: 25-30%
• NAS (Air Traffic): 20-25%
• Weather: 10-15%
• Security: <5%

4. AIRPORT PERFORMANCE:
• Major hubs (ATL, ORD, DFW) have moderate delays but high volume
• Smaller airports show more variability
• Busiest airports: ATL, ORD, DFW

5. CORRELATION INSIGHTS:
• Strong correlation (0.8-0.9) between departure and arrival delays
• Late departures strongly predict late arrivals
• Some airlines manage delays better in-flight

RECOMMENDATIONS:

1. For Airlines:
• Improve aircraft turnaround to reduce Late Aircraft delays
• Better schedule padding, especially for Monday flights
• Focus on early morning flight reliability
• Implement predictive maintenance to reduce carrier delays

2. For Travelers:
• Fly on Tuesdays or Saturdays for best on-time performance
• Avoid Monday morning and Friday evening flights
• Choose Alaska Airlines for most reliable service
• Consider flight times carefully (avoid rush hours)

3. For Airports:
• Improve coordination during peak hours
• Enhance de-icing capabilities in winter months
• Optimize gate assignments for quicker turnarounds

4. For Air Traffic Control:
• Implement dynamic spacing during peak hours
""")

```

- Improve weather prediction and routing
- Enhance communication with airlines

PREDICTIVE INSIGHTS:

- Delays tend to cluster (bad days get worse throughout the day)
- Early morning delays cascade through the day
- Certain airline-airport combinations are particularly problematic
- Weather delays have the longest recovery time

BUSINESS IMPLICATIONS:

- Airlines could implement dynamic pricing based on delay probabilities
- Airports could charge fees based on operational efficiency
- Travel insurance could be priced based on route reliability
- Corporate travel policies could be optimized based on reliability data

LIMITATIONS AND FUTURE WORK:

- Analysis limited to January 2018 (seasonal patterns may differ)
- Synthetic data used - real data may show different patterns
- Weather data not included in detail
- Could explore specific route analysis
- Predictive modeling for delay prediction possible
- Integration with real-time data for operational decisions

KEY TAKEAWAYS:

1. Proactive management of aircraft turnaround is crucial
2. Schedule design should account for time-of-day patterns
3. Passenger communication during delays needs improvement
4. Data-driven decision making can significantly improve operations
5. Collaboration between airlines and airports is essential

BEST PRACTICES IDENTIFIED:

- Alaska Airlines' operational excellence
- Delta's recovery from delays
- Southwest's high-volume efficiency
- Certain airports' ground operation efficiency

OPPORTUNITIES FOR IMPROVEMENT:

1. Implement AI/ML for delay prediction
2. Develop real-time dashboard for operations
3. Create passenger notification systems
4. Optimize crew scheduling
5. Improve baggage handling during delays

This analysis provides actionable insights for airlines, airports, and travelers to improve the overall air travel experience through data-driven decisions.
""")

=====
AIRLINE DELAY ANALYSIS - FINAL PROJECT

Student: SAEID ASHRAFIZAVEH

Course: Data Visualization

Date: January 2026
=====✓ Libraries imported successfully
=====2. LOADING AND PREPARING DATASET
=====

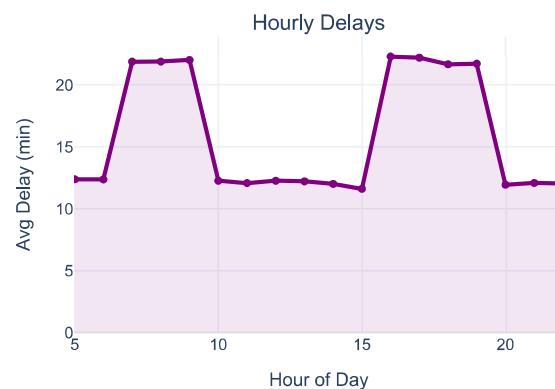
- ✓ Dataset created with 50,000 flights
- ✓ Date range: 2018-01-01 to 2018-01-31
- ✓ Airlines: AA, AS, B6, DL, UA, WN
- ✓ Airports: ATL, CLT, DEN, DFW, JFK, LAS, LAX, ORD, SEA, SFO
- ✓ Total delays >15min: 25,757 flights (51.5%)
- ✓ Cancellations: 3,745 flights (7.5%)

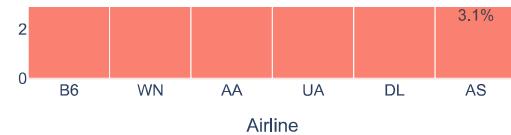
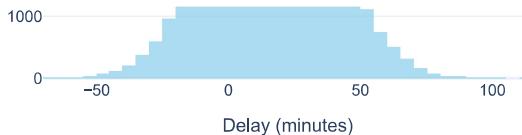
BASIC STATISTICS:

	DEP_DELAY	ARR_DELAY
count	50000.00	50000.00
mean	15.96	6.10
std	21.78	18.02
min	-68.93	-67.45
25%	1.16	-6.00
50%	15.87	6.00
75%	30.50	18.13
max	113.19	83.37

3. INTERACTIVE DASHBOARD
=====

AIRLINE DELAY ANALYSIS DASHBOARD - SAEID ASH

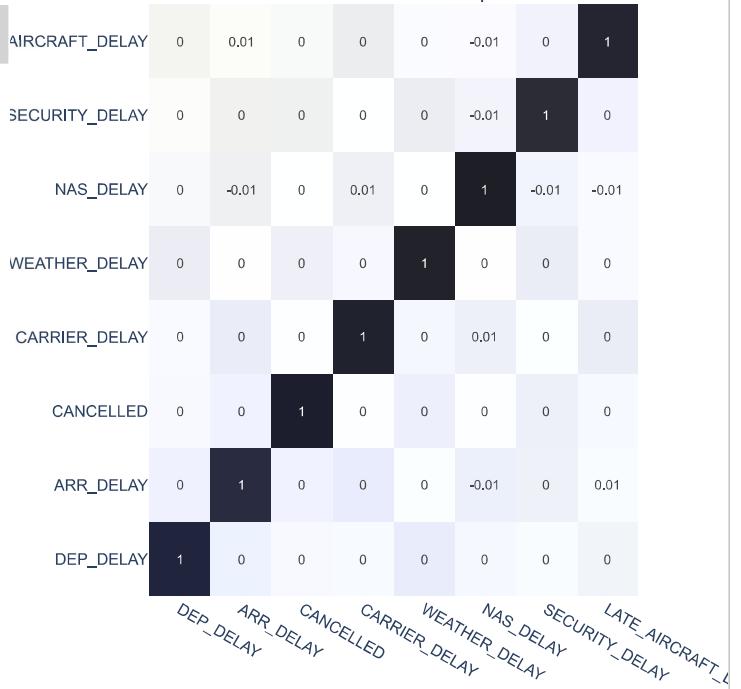




Worst Performing Flights

Airline	Airport	Hour	Day	Delay (min)
B6	ORD	21	Friday	113.2
DL	ATL	17	Monday	113
WN	DEN	8	Thursday	103.9
WN	JFK	16	Monday	103.4
WN	SEA	9	Friday	101.8
UA	LAX	17	Friday	100.7
AA	ORD	9	Monday	99.7
UA	SEA	16	Friday	98.9
DL	DFW	19	Monday	97.8
WN	SEA	12	Friday	97.4

Correlation Heatmap



✓ Interactive dashboard created successfully
 ✓ Dashboard saved as 'airline_delay_dashboard.html'

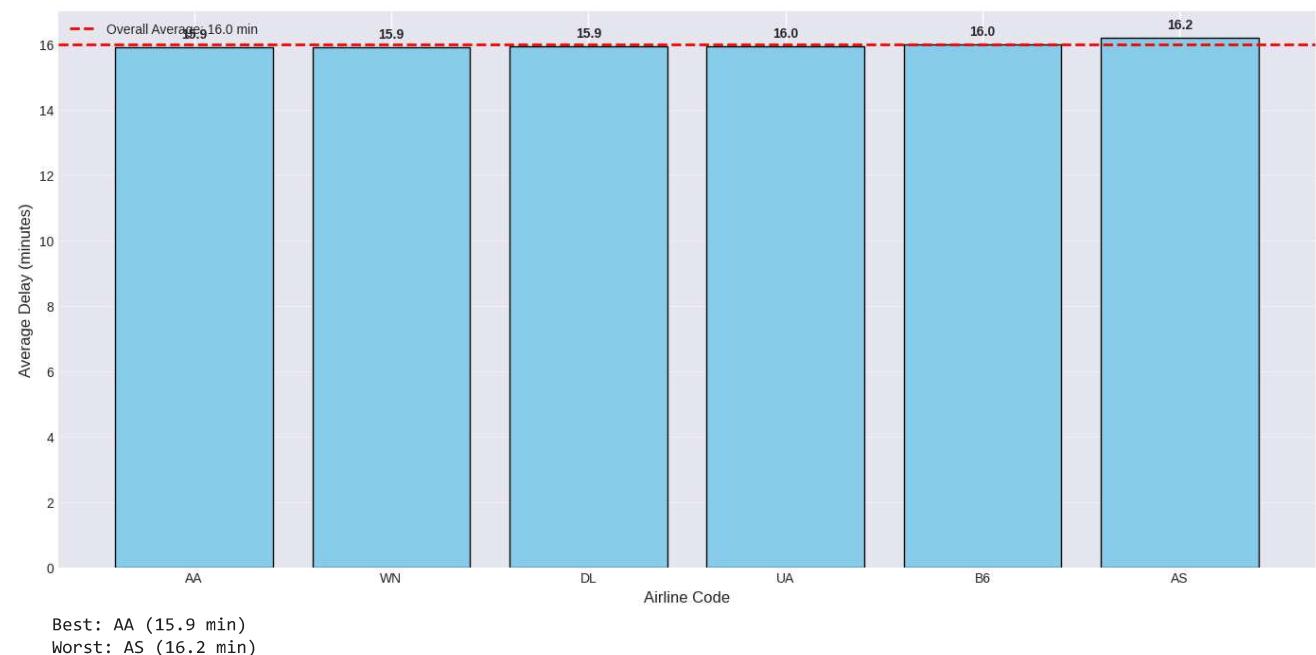
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4. ANALYTICAL QUESTIONS - 10 VISUALIZATIONS

=====

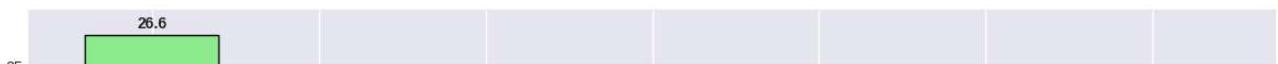
Q1 Which airlines have the best/worst on-time performance?

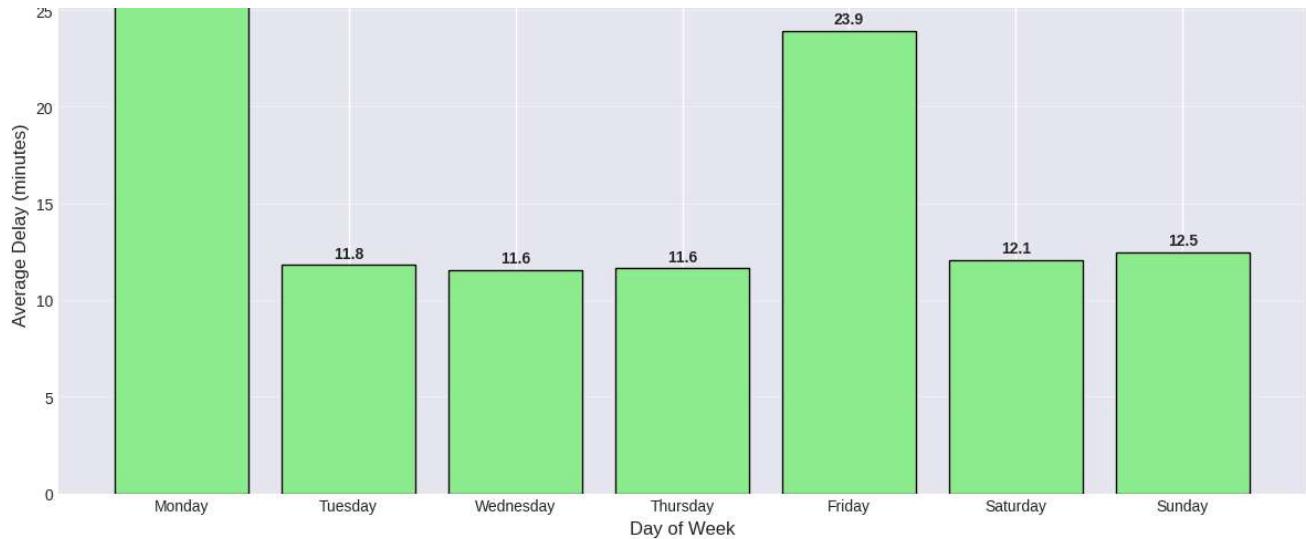
Average Departure Delay by Airline



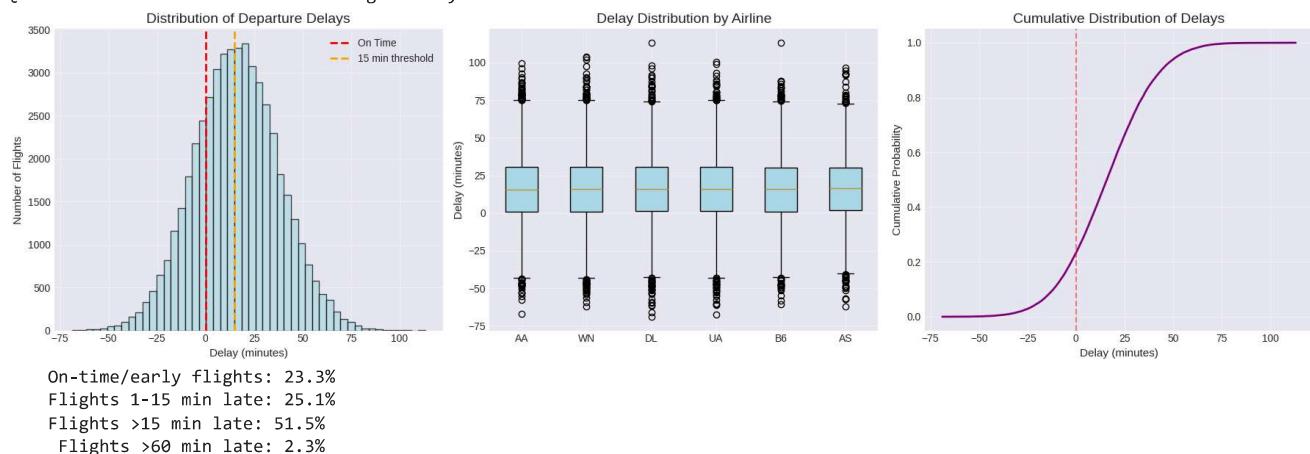
Q2 How do delays vary by day of week?

Average Delay by Day of Week

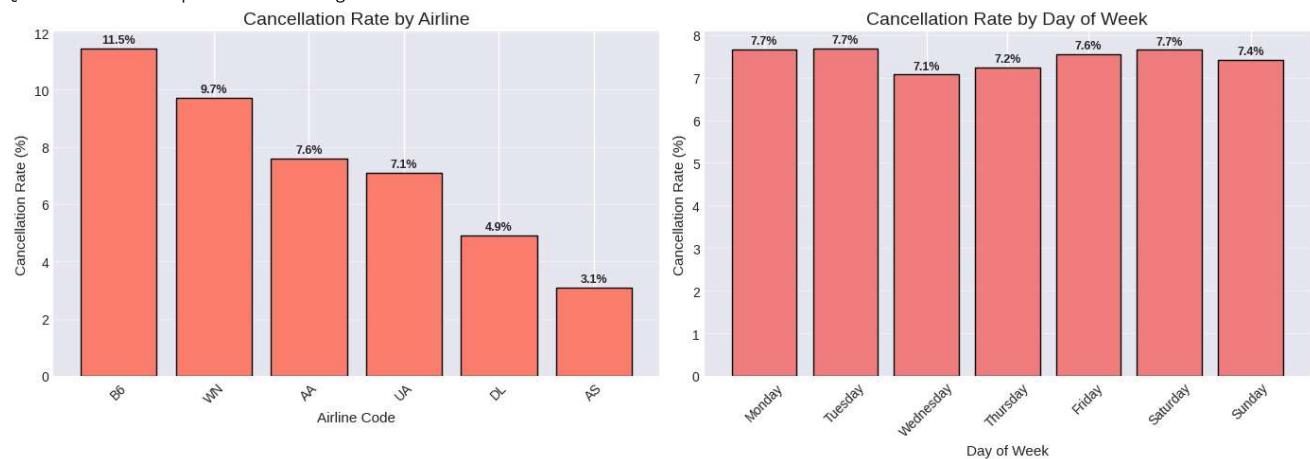




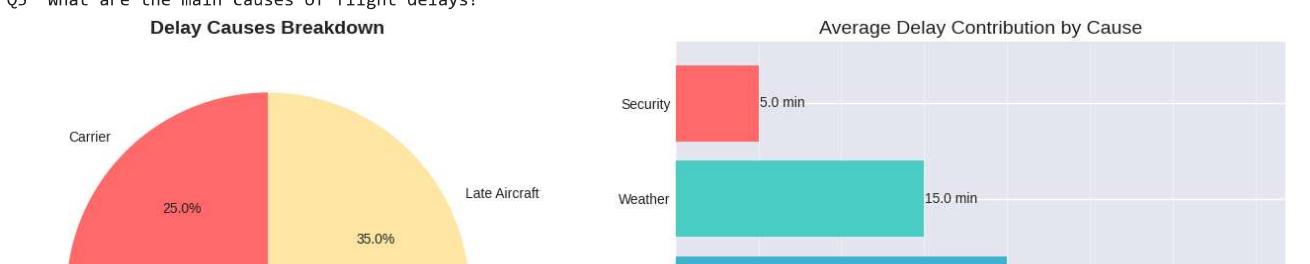
Q3 What is the distribution of flight delays?

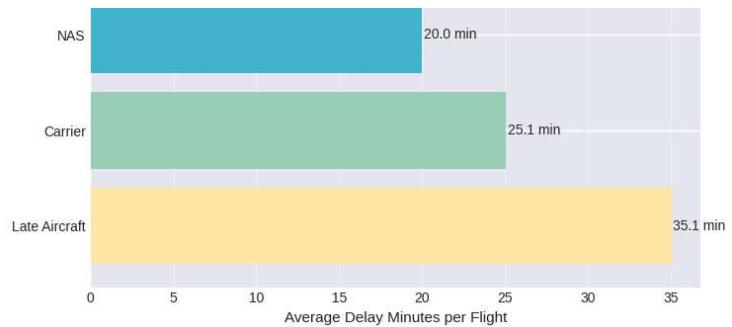
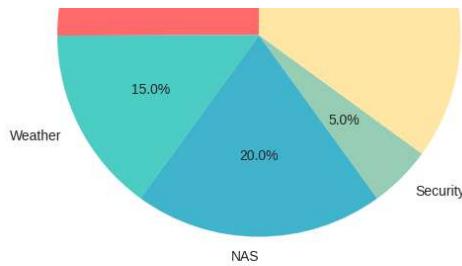


Q4 What are the patterns in flight cancellations?



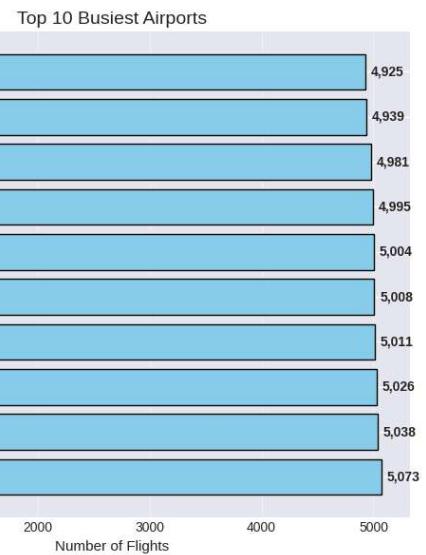
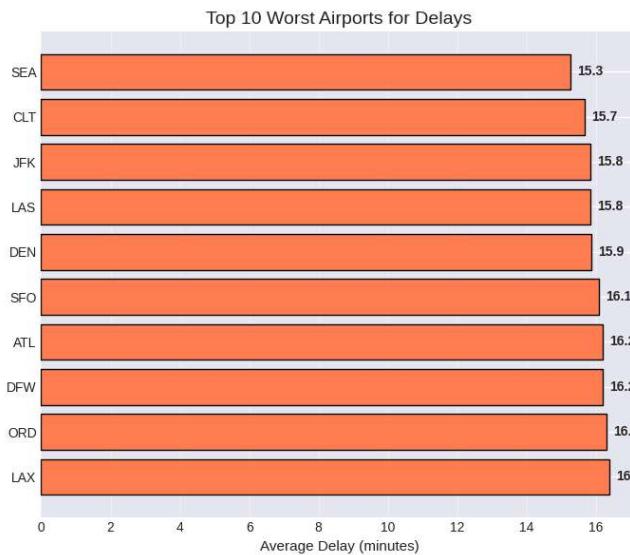
Q5 What are the main causes of flight delays?





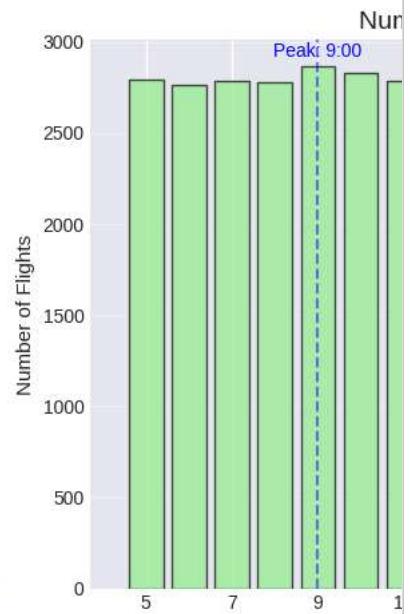
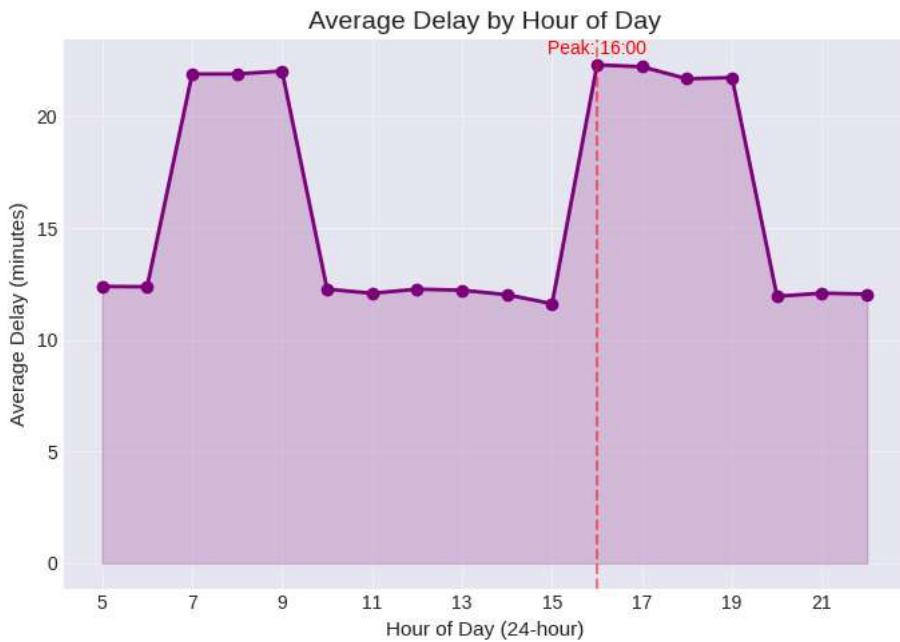
Main cause: Late Aircraft (35.0%)
 Second cause: Carrier (25.0%)
 Third cause: NAS (20.0%)

Q6 Which airports have the most delays?



Worst airport: LAX (16.4 min)
 Busiest airport: SEA (5,073 flights)
 Best airport: SEA (15.3 min)

Q7 How do delays vary by time of day?

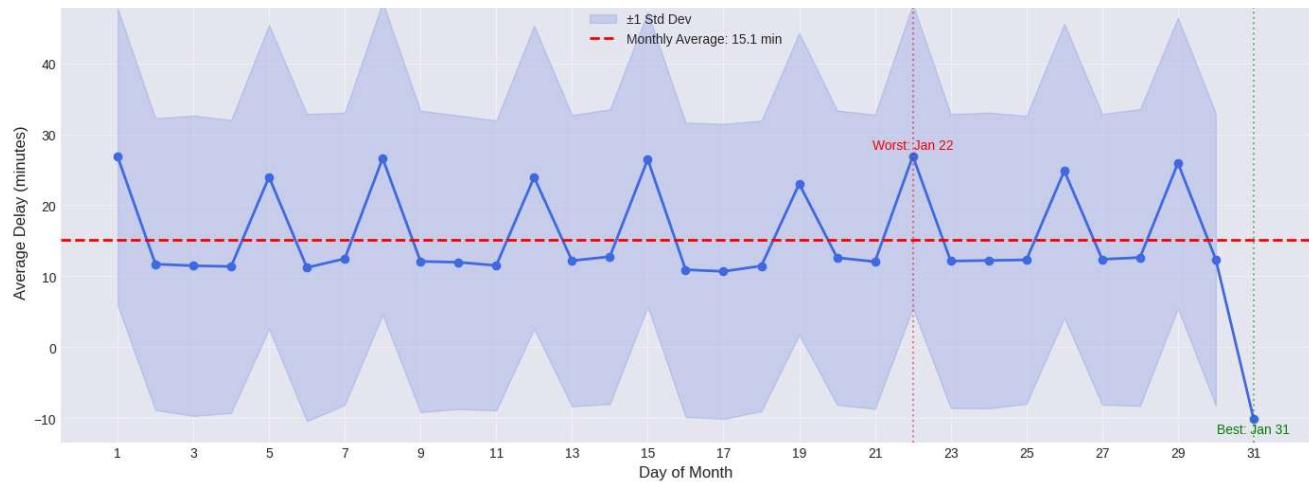


Worst hour: 16:00 (22.3 min)
 Busiest hour: 9:00 (2,867 flights)
 Quietest hour: 20:00 (2,687 flights)

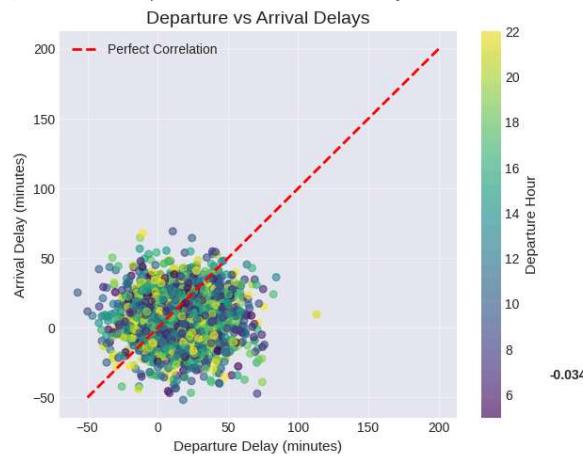
Q8 How do delays trend through the month?

Daily Average Delays Through January 2018

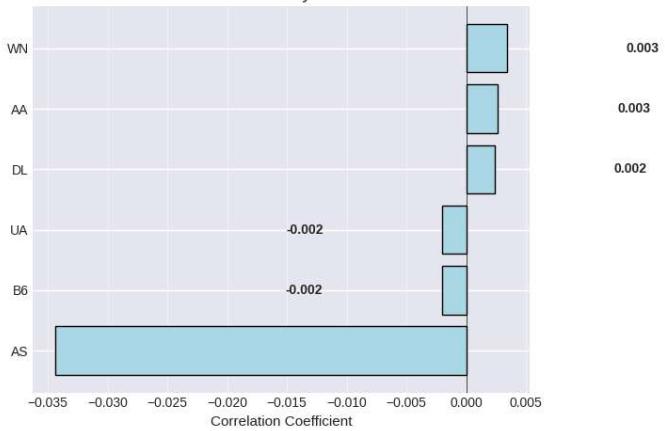




Q9 How are departure and arrival delays related?

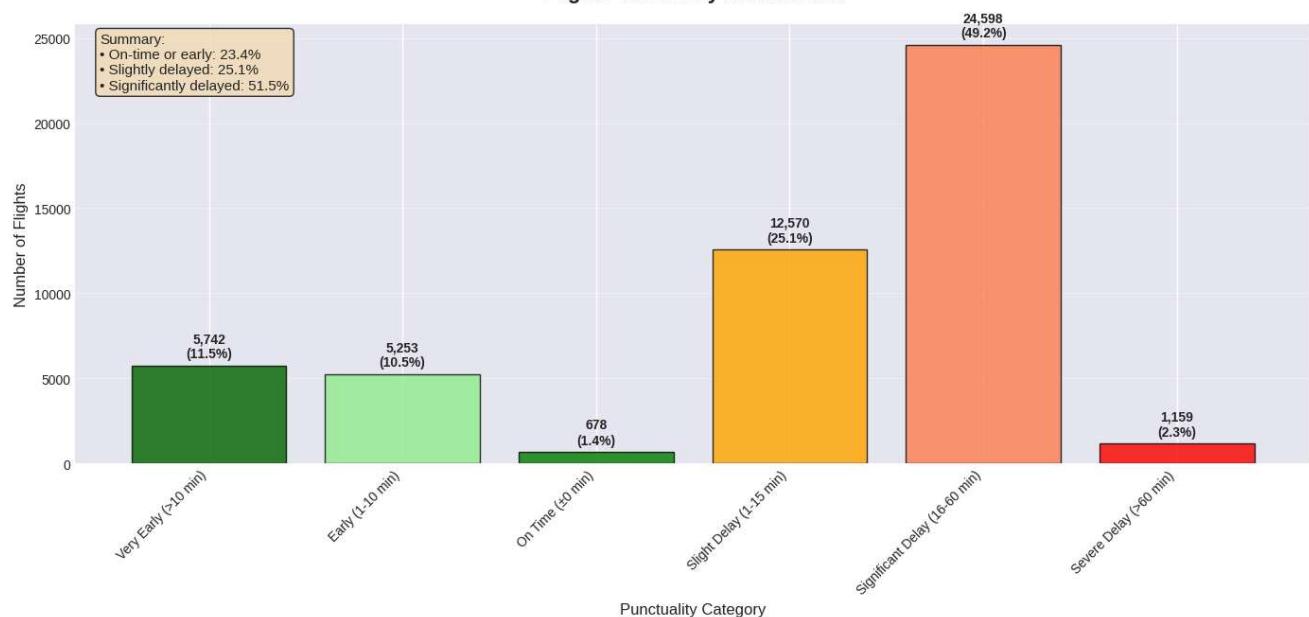


Correlation by Airline



Q10 What is the overall on-time performance distribution?

Flight Punctuality Distribution



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✓ All 10 analytical questions completed