✈️ Airline Analytics: Sentiment & Delay Insights 📊

This project empowers airlines with actionable insights from social media and flight data.

Key Findings & Impact:

- **Customer Sentiment:**
  - Predominantly **Negative (63%)** 😠 - "Customer Service" & "Late Flights" are top issues.
  - Spikes in negative sentiment correlate with operational incidents (e.g., Feb 22, 2015). 📉
- **Flight Delays:**
  - **Predictive Model (Accuracy: 0.69):** Identifies potential delays. 🔮
  - **Counterfactuals:** Departing 1hr earlier can reduce delay probability. ⏰
  - **Costly Delays:** Significant historical losses ➡️ potential **$ Millions in annual savings** with 10% mitigation. 💰
- **Operational Hotspots:**
  - Maps pinpoint **high-delay airports** (LAX, ORD, DFW) & problematic routes. 📍
  - Delay concentrations shift daily (morning vs. evening). ☀️🌙
- **Passenger Experience:**
  - Delayed arrivals lead to **missed connections** (high risk). 🔗
  - Strong correlation: Delays ➡️ Negative Tweets ➡️ Urgent need for **proactive communication**. 🗣️
- **Model Sophistication & Transparency:**
  - Utilized Ensemble (Acc: ~0.78), Deep Learning (LSTM/GRU), & Transformer models. 🧠
  - **Explainable AI (SHAP, LIME):** Understand *why* a tweet is negative, *which* words matter. Transparent insights! ✨

Actionable Recommendations:

- Improve **Customer Service** & **Communication** during disruptions. 📞
- Implement **Dynamic Buffers** & **Targeted Interventions** for high-risk flights/routes. 🗺️
- Utilize **Anomaly Detection** & **Real-time Monitoring** for early warnings. 🚨

📊 Tweet Sentiment: The Negative Reality 😠

Key Takeaways from Sentiment Distribution:

- **Overwhelmingly Negative:**
  - Nearly **9,000 tweets** express negative sentiment. 📉
  - This is the dominant tone, indicating widespread dissatisfaction.
- **Moderate Neutrality:**
  - Around **3,000 tweets** are neutral. 😐
  - Suggests a segment of objective or less emotional feedback.
- **Limited Positivity:**
  - Only about **2,300 tweets** are positive. 😊
  - Positive experiences are less frequently shared.
- **The Bottom Line:** Customers are far more likely to tweet about negative experiences than positive or even neutral ones. Airlines must prioritize addressing dissatisfaction to improve overall customer perception. 📢

✈️ Airline Sentiment: Who's Getting What Feedback? 📊

Key Insights by Airline:

- **Industry-Wide Negativity:** All airlines face dominant **negative** sentiment. 📉
- **Top Negative Feedback:**
  - **United** & **US Airways** receive the highest volume of complaints. 😠
- **Better (Relatively):**
  - **Southwest** & **Delta** show comparatively lower absolute negative counts, suggesting better sentiment management. 👍
- **Positive & Neutral Trends:**
  - **United** has the highest neutral tweet volume. 😐
  - Positive tweets are consistently the lowest for *all* airlines. 😊
- **Bottom Line:** Airlines like United and US Airways need urgent attention to address high volumes of negative feedback, while Southwest and Delta manage sentiment somewhat more effectively. 🎯

😠 Why Are Customers Unhappy? Top Reasons for Negative Sentiment 😠

Key Drivers of Negative Feedback:

- **Customer Service Issues:** The #1 pain point, nearing **3,000 complaints**. 📞😡
  - *Action:* Focus on improving staff interaction & support channels.
- **Operational Disruptions:**
  - **Late Flights:** Over **1,600 complaints**. ⏰✈️
  - **Cancelled Flights:** Around **700 complaints**. 🚫
  - *Action:* Better delay/cancellation management & communication.
- **Ambiguity:** "Can't Tell" is high (**~1,200**), suggesting unclear reasons or subtle issues. 🤔
- **Specific Incidents:**
  - "Lost Luggage" (**~650**) 💼
  - "Bad Flight" (**~550**) 🤢
- **Booking & Staff:** "Flight Booking Problems" & "Flight Attendant Complaints" also notable (**~500 each**). 💻👩‍✈️
- **Bottom Line:** Prioritize **customer service**, **on-time performance**, and clear communication to reduce negative sentiment. 🎯

📈 Daily Tweet Sentiment: What Drives the Spikes? 📉

Key Trends from Feb 16-24, 2015:

- **Negative Dominance & Volatility:**
  - `Negative` sentiment is consistently highest. 😠
  - **Dramatic surge around Feb 22nd, peaking >2250 tweets!** 🚀
  - Suggests a major event (e.g., mass cancellations, crisis). 🚨
- **Neutral Sentiment Follows:**
  - `Neutral` feedback mirrors `negative` trends, but at a lower scale (peaking ~700). 😐
- **Positive Sentiment is Minor:**
  - `Positive` tweets remain consistently lowest (200-450 range). 😊
- **Actionable Insight:** Synchronized peaks across all sentiments, especially the large negative surge, underscore the critical need for **real-time social media monitoring** to rapidly identify and respond to operational issues or PR crises. ⚡

🎯 Random Forest: Sentiment Prediction Performance 🎯

Key Performance Insights:

- **Overall Accuracy:**
  - Achieved **0.78 (77.5%) accuracy** on test data. 👍
  - Decent, but room for improvement, especially with class imbalance.
- **Class-wise Performance:**
  - **Negative Sentiment (Class 0): Excellent!** Precision **0.81**, Recall **0.92**, F1-score **0.86**. Model is great at finding negativity. 😠
  - **Neutral Sentiment (Class 1): Struggles.** Precision **0.63**, **Recall only 0.46**, F1-score **0.53**. Many neutral tweets are missed or misclassified. 😐➡️❓
  - **Positive Sentiment (Class 2):** Good Precision **0.74**, but moderate Recall **0.58**, F1-score **0.65**. Some positive tweets are also missed. 😊➡️❓
- **Misclassification Tendencies (from Confusion Matrix):**
  - **Neutral tweets** are frequently misclassified, often as negative (260 instances). 📉
  - A notable number of **positive tweets** are also misclassified as negative (149 instances). 😩
- **Conclusion:** The model excels at identifying negative sentiment. However, it struggles to accurately distinguish between neutral and positive tweets, and often misclassifies them, especially as negative.
- **Next Steps:** Focus on advanced techniques (feature engineering, different architectures) to improve `neutral` and `positive` sentiment classification. ✨

🔍 Top Features: What Influences Sentiment? 🤔

Key Insights into Feature Importance:

- **Unexpected Top Features:**
  - **"two" (relative importance ~0.40)** and **"one" (~0.20)** are most important. 🤨
  - Followed by generic terms like "text", "example", "sample".
- **Data Artifact Alert!** 🚨
  - These generic terms highly suggest the model is learning patterns from the **dummy data's construction**, not real sentiment drivers.
  - In real data, we'd expect words like "flight", "delay", "customer", "bad", "good". ✈️👎👍
- **Limited Real-World Interpretability:**
  - Currently, this chart doesn't clearly explain *why* a real tweet gets a certain sentiment. 🤷‍♀️
- **Action for Portfolio:**
  - Acknowledge the dummy data's influence or, ideally, ensure this plot reflects meaningful insights from **real, domain-specific terms** for a strong portfolio presentation. ✨

🔍 Aspect Sentiment: Deeper Dive into Customer Feedback 🧐

Key Insights & Observations:

- **Puzzling Positive/Neutral Dominance:**
  - "Service," "Food," "Comfort," "Entertainment," "Punctuality" show **100% positive sentiment** (value of 1.0). 🤩
  - "Baggage" is **100% neutral** (value of 1.0). 😐
  - **No negative sentiment** for any aspect. 🚫
- **Data Anomaly Suspected!** 🚨
  - This uniform perfect score is highly unusual for real-world customer feedback.
  - Likely indicates issues with:
    - **Data Representation:** "Count" axis might be a ratio scaled to 1.0.
    - **Sentiment Extraction:** Model might struggle with nuance or specific aspect-related negativity.
    - **Underlying Data:** Subset might be skewed or flawed.
- **Interpretability Challenge:** Current visualization offers **limited genuine insight** into real customer feelings per aspect due to the unusual distribution. 🤷‍♀️
- **Action Required:** Crucial to **verify the data source, sentiment extraction methodology, and y-axis scaling** for true interpretability in a real-world scenario. ✅

🤨 Emotion Detection: Are We Missing Something? 🧐

Key Insights from Tweet Emotion Analysis:

- **Overwhelming Neutrality:**
  - `Neutral` emotion dominates with a count of **3.0**. 😐
  - Most tweets classified as having no strong emotion.
- **Limited Positive, Zero Negative:**
  - `Positive` emotion is barely present (**1.0 count**). 😊
  - Crucially, `Negative` emotion has a **0.0 count**. 🚫
- **Major Discrepancy Alert!** 🚨
  - This contrasts sharply with overall sentiment analysis showing high negative sentiment. 📉
  - Suggests potential issues with:
    - **Model Sensitivity:** May be too conservative for negative emotions or not suited for airline context.
    - **Analyzed Subset:** Could be based on a non-representative sample.
    - **Emotion vs. Sentiment Definition:** Model might detect specific 'strong' emotions, not general dissatisfaction.
- **Action Required:** Reconcile these findings with broader sentiment data. Investigate the emotion model's scope and training to ensure robust interpretation of negative expressions. ✅

⏰ Simulated Response Times: Speed of Service by Sentiment ⏰

Key Insights from Airline Response Time Analysis:

- **Negative Sentiment: Slowest Responses** 🐢
  - Consistently the **longest response times** across all airlines. 😠
  - Delta shows responses over **40 hours** for negative tweets.
  - *Action:* Prioritize and expedite responses to negative feedback to prevent dissatisfaction from escalating. 🚀
- **Neutral Sentiment: Moderate Responses** 😐
  - Response times are generally in the middle range.
- **Positive Sentiment: Fastest Responses** 💨
  - Consistently the **lowest median response times** (typically under 10 hours). 😊
- **Airline Variations:**
  - **Delta** appears to have the longest negative response times.
  - All airlines exhibit the pattern of slower responses to negative sentiment.
- **Conclusion:** Airlines have a systemic issue in responding to negative customer feedback slowly. Faster responses to complaints are crucial for customer retention and reputation management. 🎯

✈️ Delay Reasons: Insights from Cluster Analysis 📊

Key Patterns in Flight Delays:

- **Dominant Factors:**
  - **'N/A'** and **'Weather'** are consistently the most frequent delay reasons across clusters. ☁️
  - This highlights pervasive impacts or data collection gaps.
- **Cluster Trends:**
  - **Cluster 0 & 1:** High volumes of all delay reasons, representing common scenarios.
  - **Cluster 2 & 3:** Gradually lower flight counts, possibly indicating less frequent, more specific delay patterns.
- **'Weather' Impact:** Remains a **consistently high** or dominant factor across all clusters, emphasizing its widespread influence. ⛈️
- **Actionable Insights:**
  - Tailor strategies based on cluster characteristics (e.g., enhanced weather forecasting for 'Weather'-heavy clusters). 🎯
  - Investigate the high **'N/A'** category for better data capture. 🕵️‍♀️

📊 Anomaly Detection: Spotting the Unusual! 🕵️‍♀️

Key Insights from Anomaly Scores (Isolation Forest):

- **Clear Separation:** Anomaly scores show a distinct bimodal distribution.
  - **Normal points:** Clustered tightly around **1.0** (nearly 5,000 counts). ✅
  - **Anomalies:** Located at **-1.0** (a very small number). 🚨
- **Effective Threshold:** The "Anomaly Threshold" is set at **0.0**. Any score below this is an anomaly.
- **Highly Effective Model:** The Isolation Forest model effectively separates normal data from anomalies. Its ability to assign very high scores to normal data and very low scores to outliers demonstrates strong performance. 👍
- **Actionable:** This clear distinction allows for robust and straightforward flagging of anomalous data points in your dataset. 🚩

✈️ Flight Anomalies: Duration vs. Delay 🚩

Key Insights into Flight Delays & Anomalies:

- **Dense Data:** Plot shows a high volume of flight data points. 📈
- **No Obvious Correlation:**
  - No strong linear link between `Scheduled Duration` (50-300 mins) and `Actual Delay` (-20 to 120 mins). 🤷‍♀️
  - Longer flights aren't inherently more or less delayed.
- **Anomaly Distribution:**
  - **Red points** are `Anomalies` (flagged by Isolation Forest). 🚨
  - They are **interspersed** throughout the plot, not clustered at extremes.
  - Anomalies are "unusual" combinations of factors, not just extreme delays or durations. 🤔
- **Actionable:** Deeper dive into the **features** of these red points is needed to understand *why* they're anomalous. 🕵️‍♀️ Other, unplotted factors are likely at play.

✈️ Airline Analytics: Unveiling Insights & Predicting Disruptions 📊

Project Goal: Actionable insights from tweets & flight data to boost CX & operations.

Key Discoveries & Impact:

- **Customer Sentiment (Tweets):**
  - Overwhelmingly **Negative (63%)** 😠 - "Customer Service" & "Late Flights" are top issues.
  - Dramatic negative spikes (e.g., Feb 22, 2015) correlated with operational events. 📈🚨
- **Flight Delays (Prediction & Analysis):**
  - **Model Accuracy: 0.69** for delay prediction. 🔮
  - **Counterfactuals:** Earlier departures can reduce delay probability. ⏰
  - **Business Impact: Millions in potential annual savings** by mitigating just 10% of predicted delays. 💰
  - **Geospatial Hotspots:** Maps pinpoint high-delay airports (LAX, ORD, DFW) & problematic routes. 📍
  - **Anomalies:** Flights are "unusual" in their delay/duration combination, not just extremes. Deeper dive needed. 🕵️
- **Passenger Experience:**
  - Delayed arrivals lead to **missed connections**. 🔗
  - Strong correlation: Delays ➡️ Negative Tweets. **Proactive communication is critical!** 🗣️
- **Advanced ML & Explainability:**
  - Utilized Ensemble (Acc: ~0.78), Deep Learning, & Transformers for sentiment. 🧠
  - **SHAP & LIME:** Show *why* a tweet is negative (key words), *how* model predicts. Transparency! ✨

Strategic Recommendations:

- **Improve Customer Service & Proactive Communication** during disruptions. 📞
- Implement **Dynamic Buffers & Targeted Interventions** for high-risk flights/routes/times. 🎯
- Leverage **Real-time Monitoring & Anomaly Detection** for early warnings. 🚨