Bumpy Airways

Would you fly with us?

Mini Project 3 by I. Font

Dataset
Method
Aim
Results
Future improvements

Aim

Use unsupervised learning (clustering and PCA) to uncover patterns in airline passenger behaviour and satisfaction levels, and identify meaningful passenger segments.

Back

The Dataset

airline_passenger_satisfaction.csv from Maven Analytics

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Customer information

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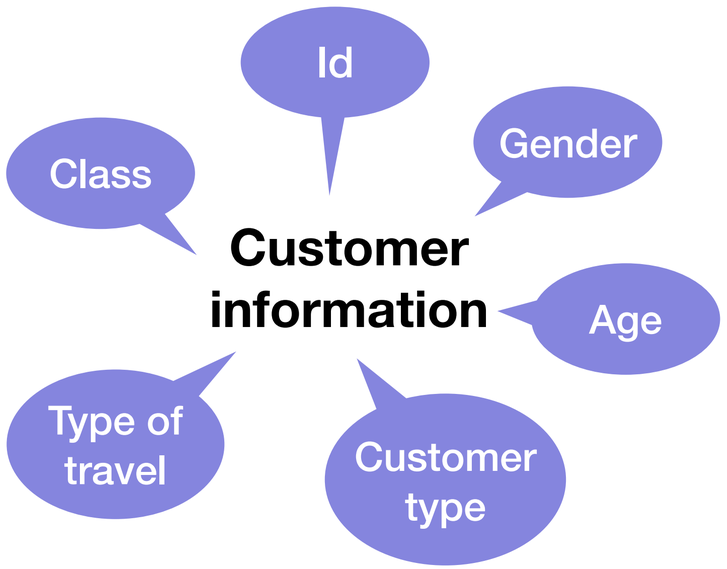

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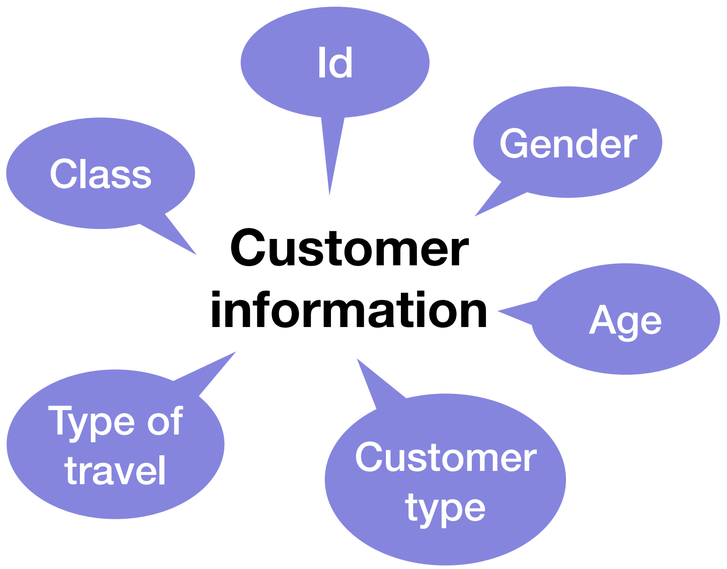

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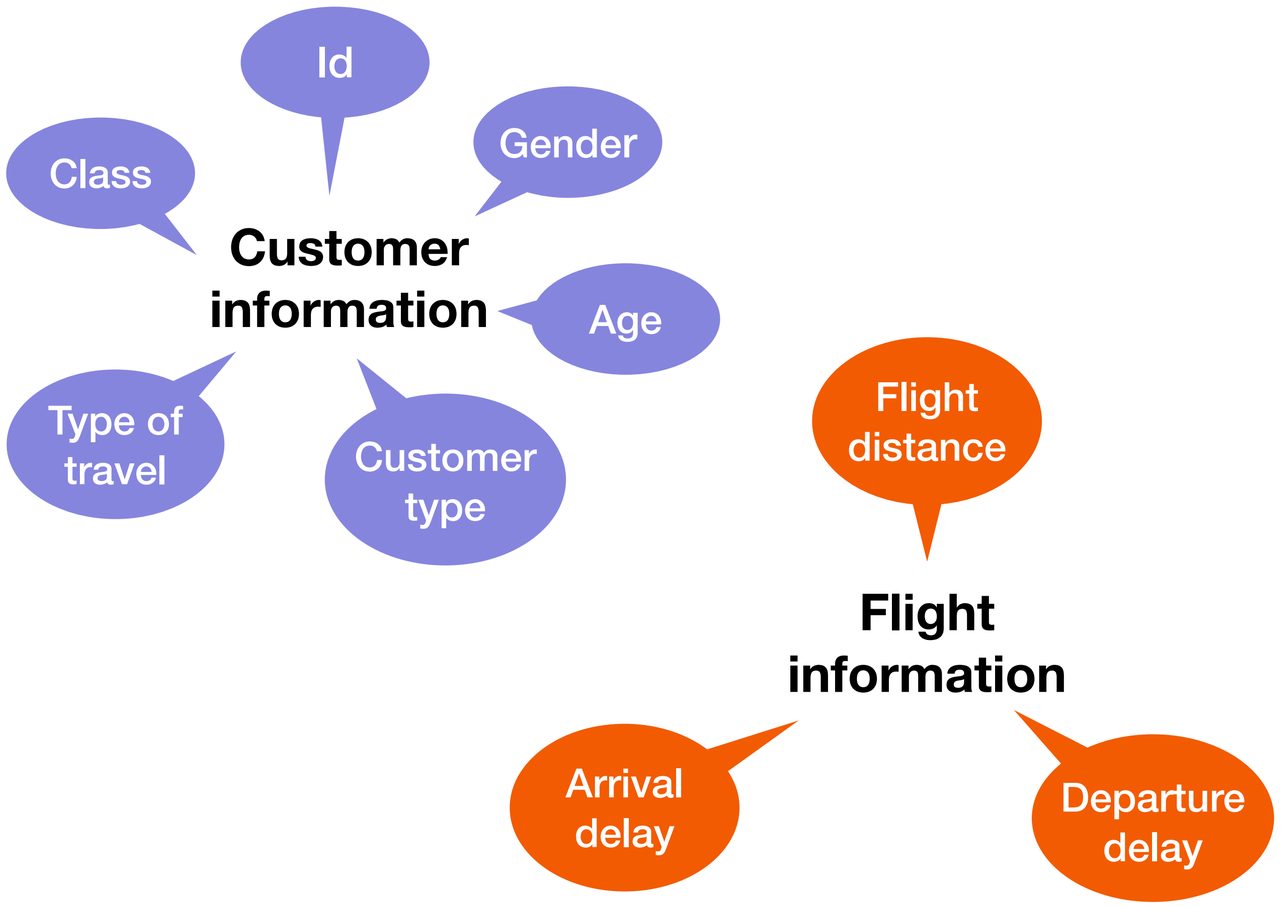

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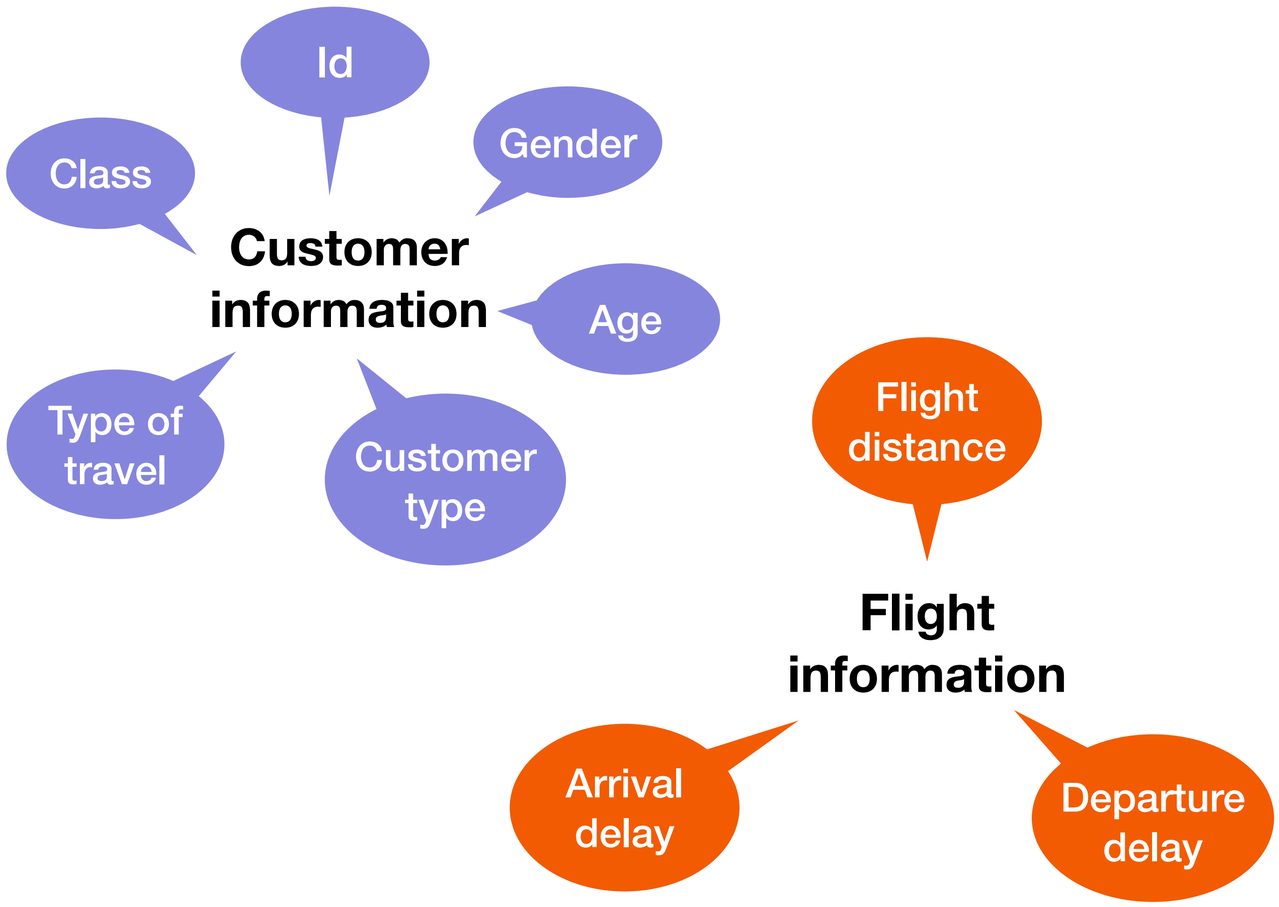

Satisfaction levels

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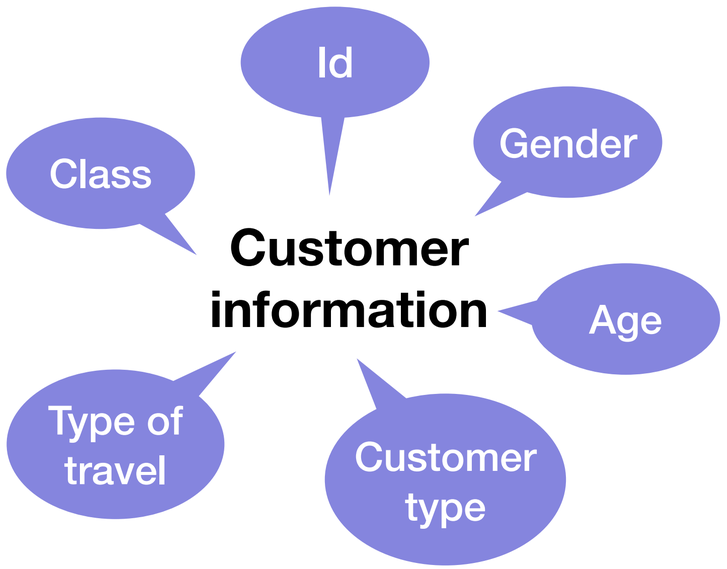

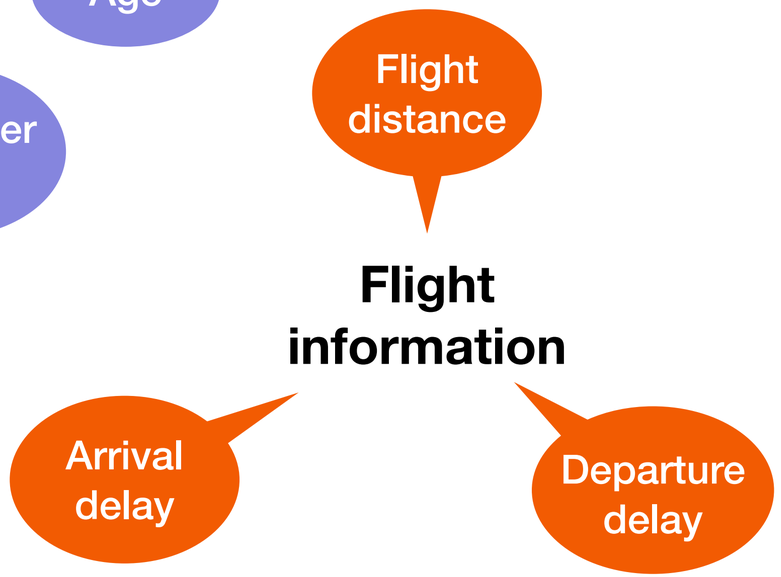

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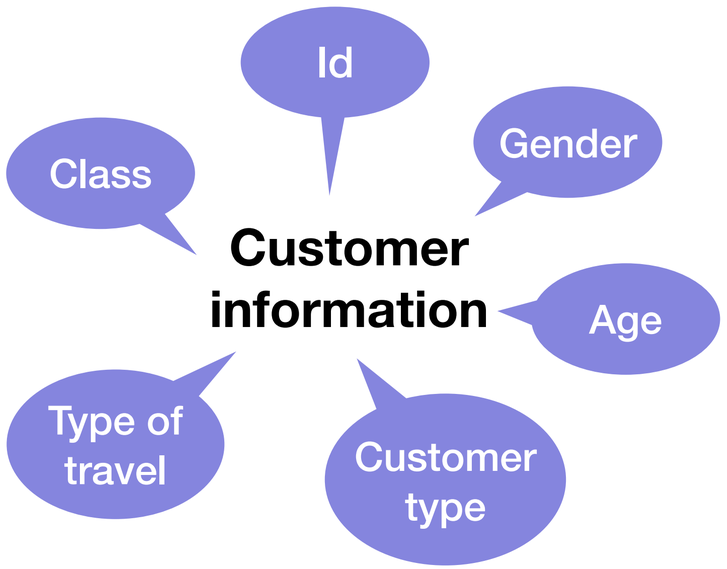

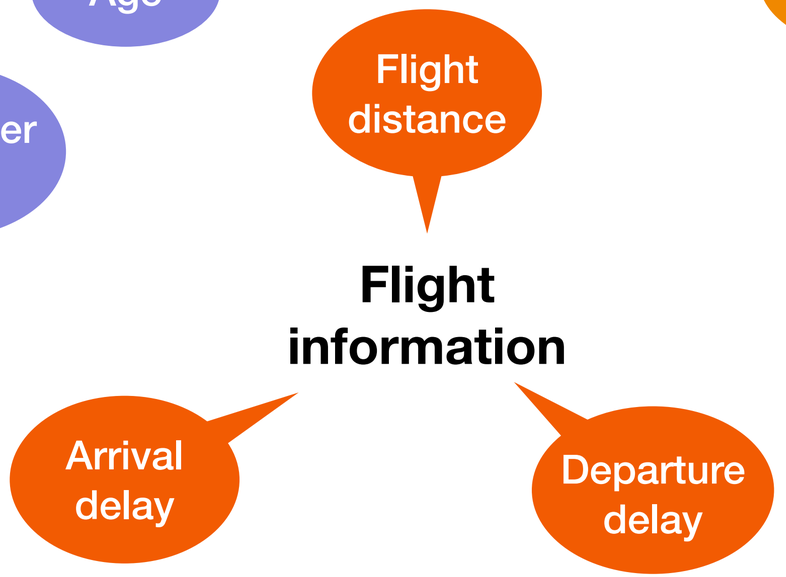

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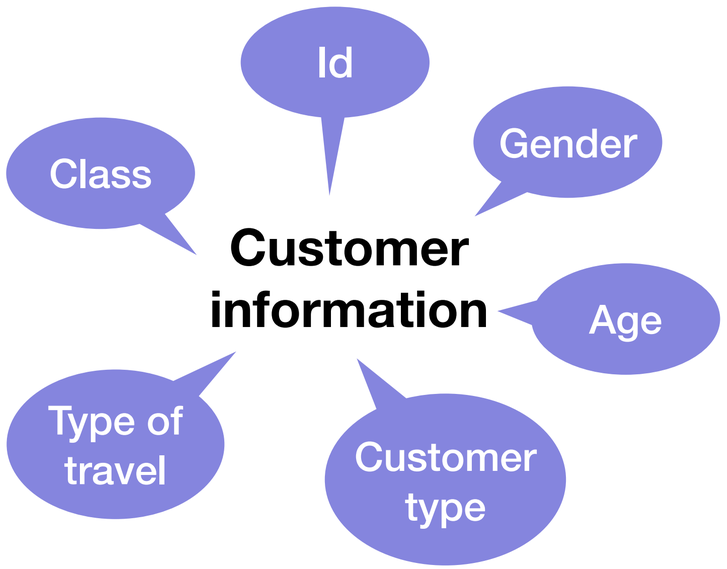

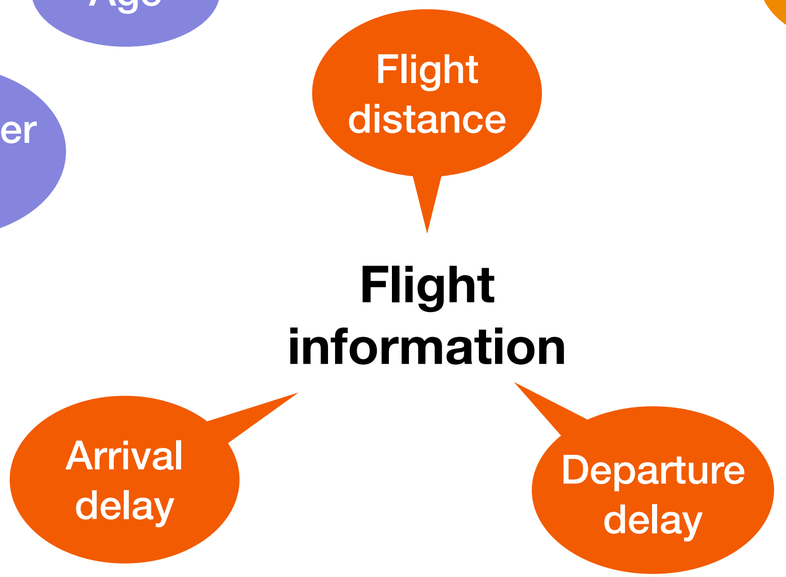

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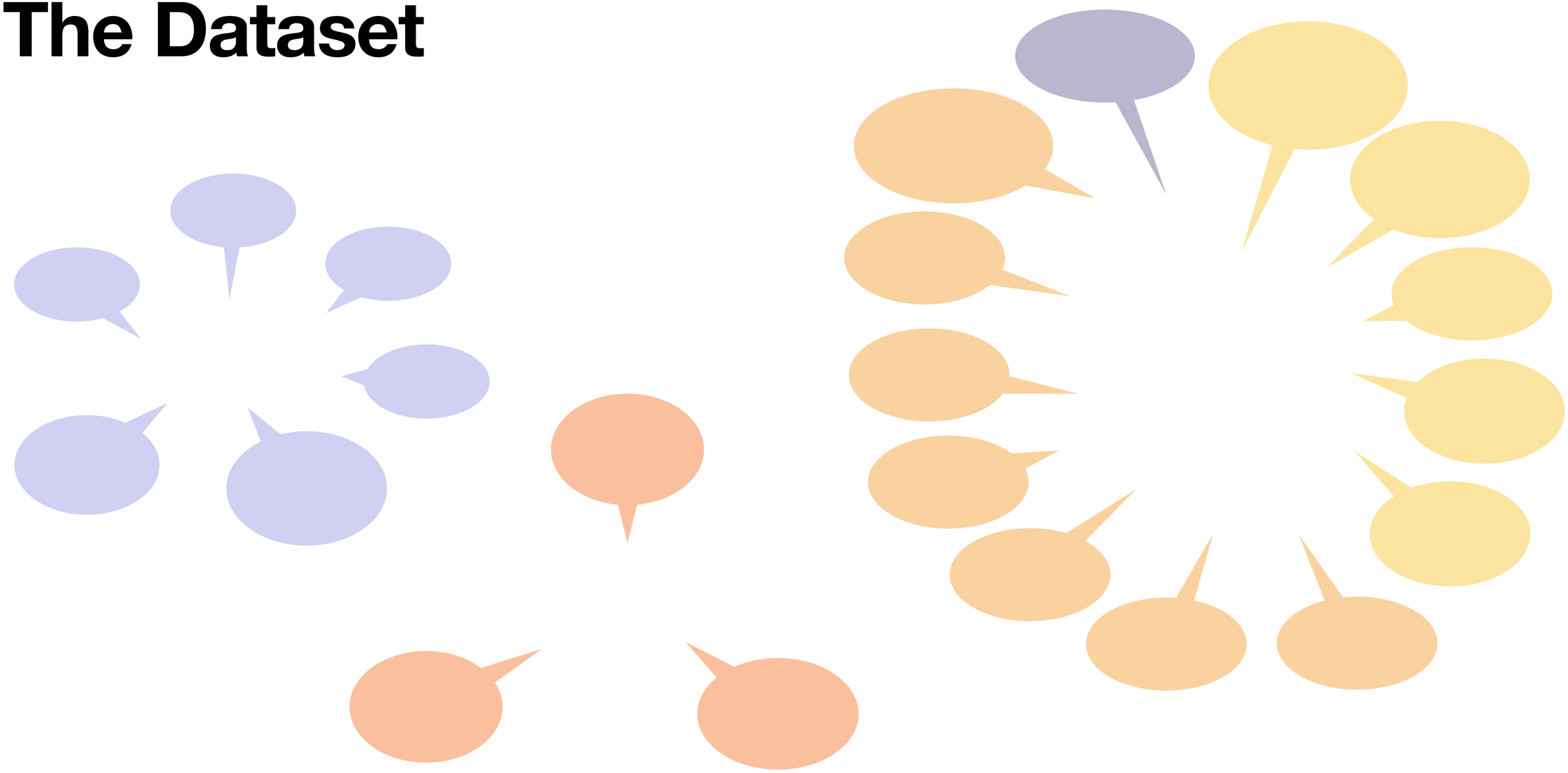

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KMeans cluster analysis

PCA dimensionality reduction analysis

HDBSCAN cluster analysis

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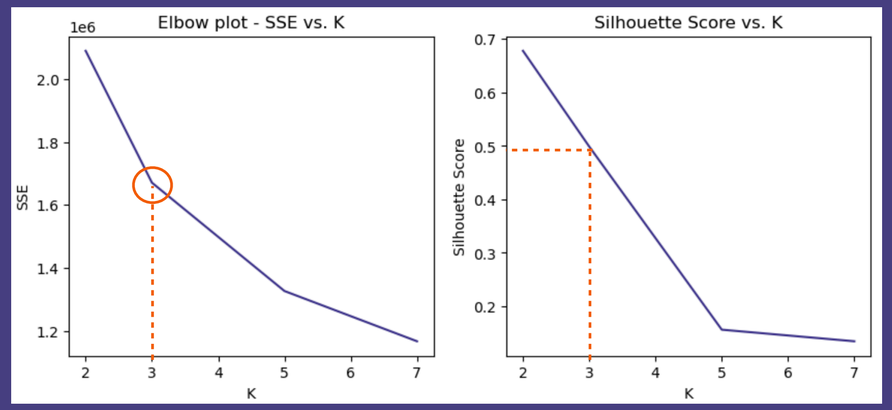

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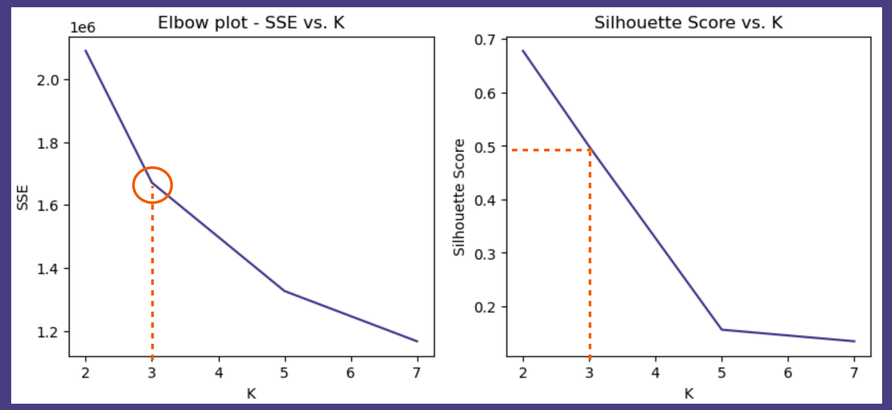

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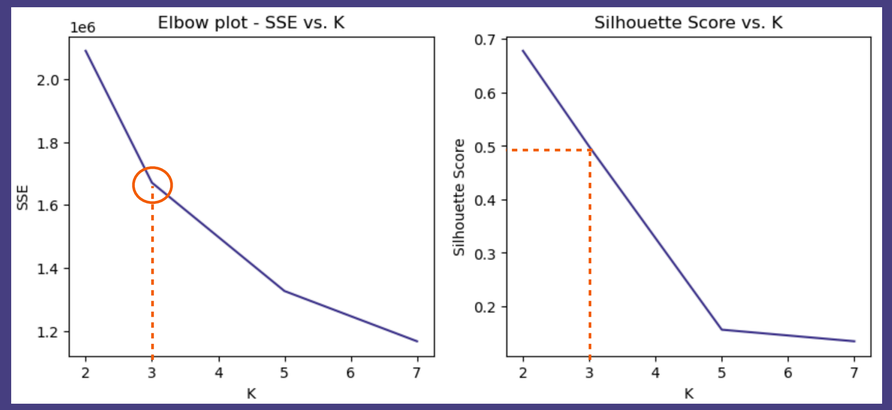

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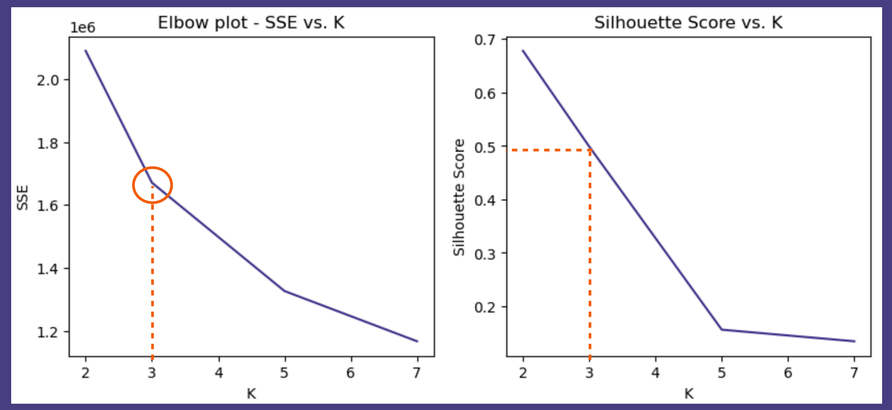

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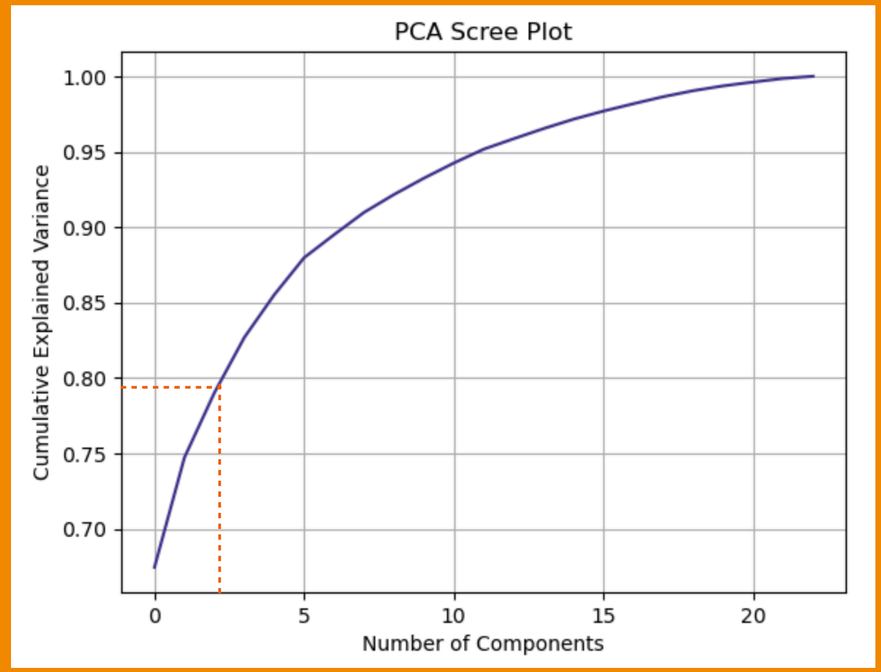

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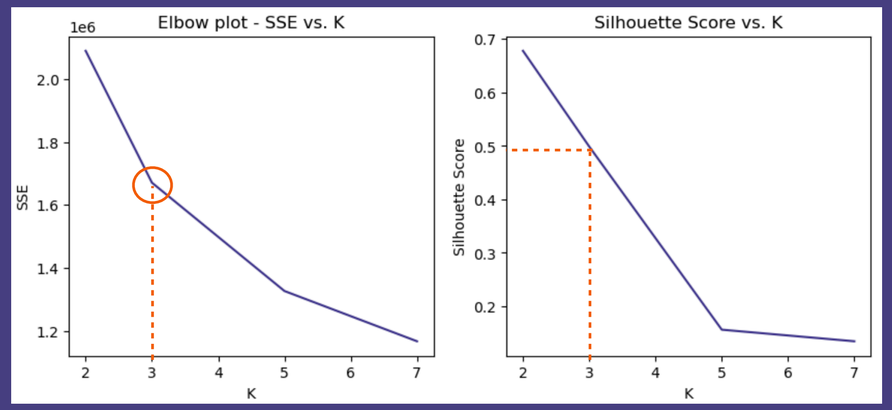

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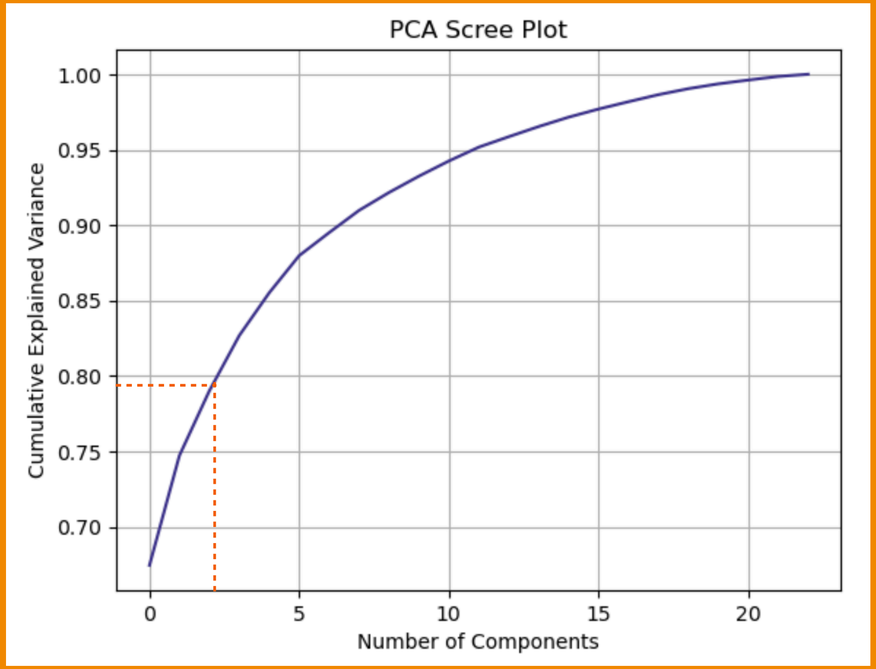

- 3 components explain about 80% of variance

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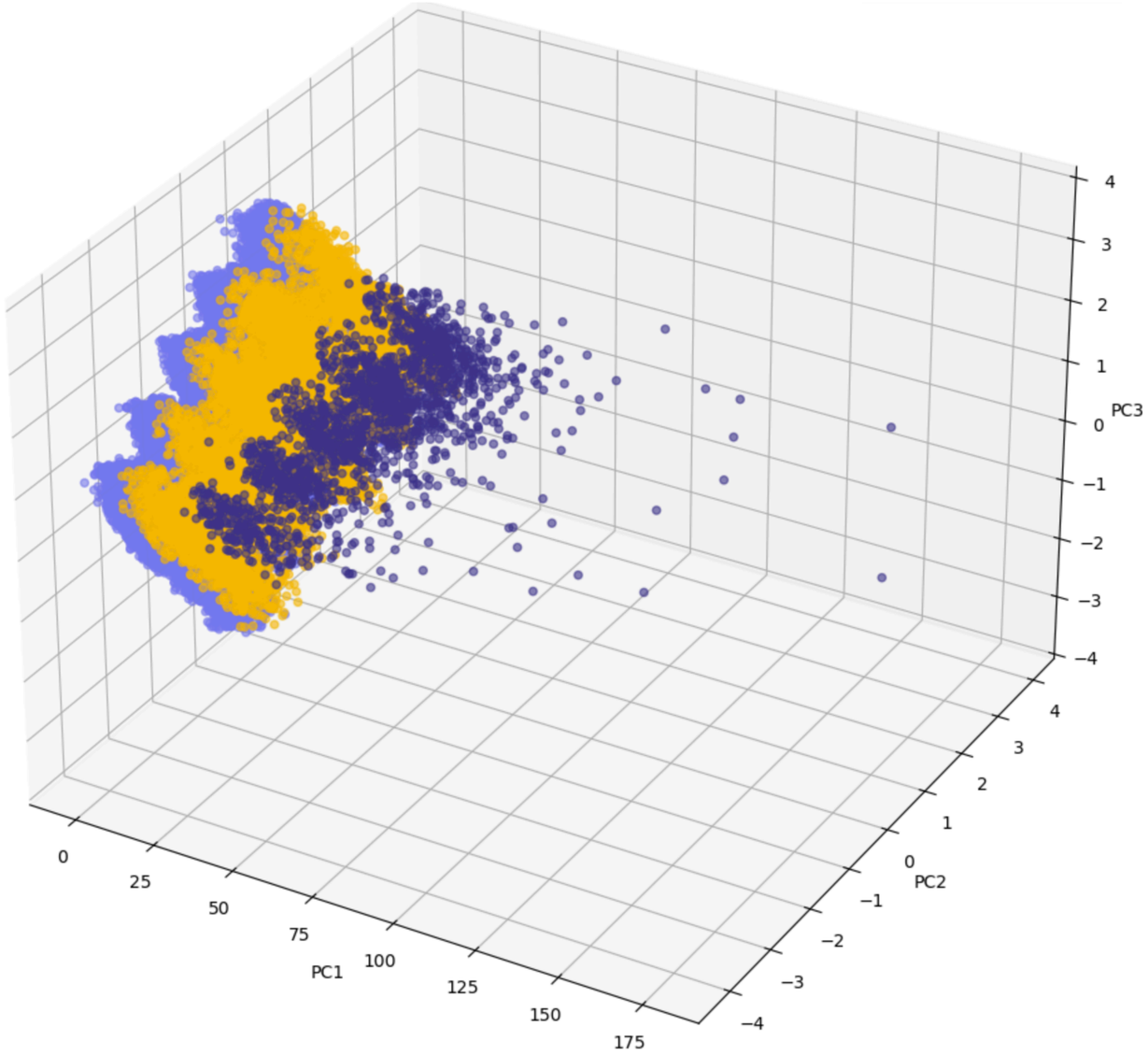
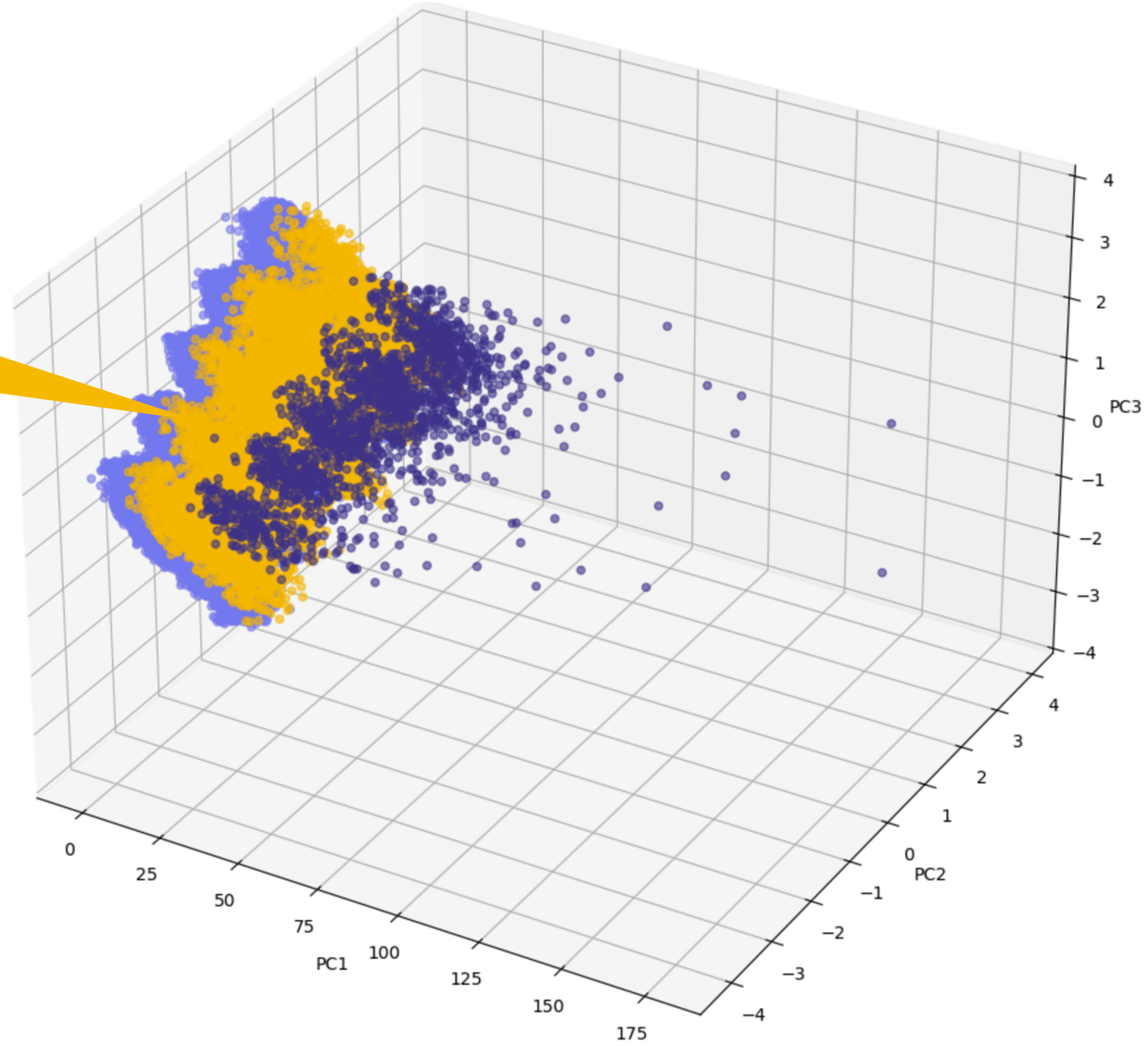
KMeans clusters



KMeans clusters

Big cluster (115711) dominated by business return customers



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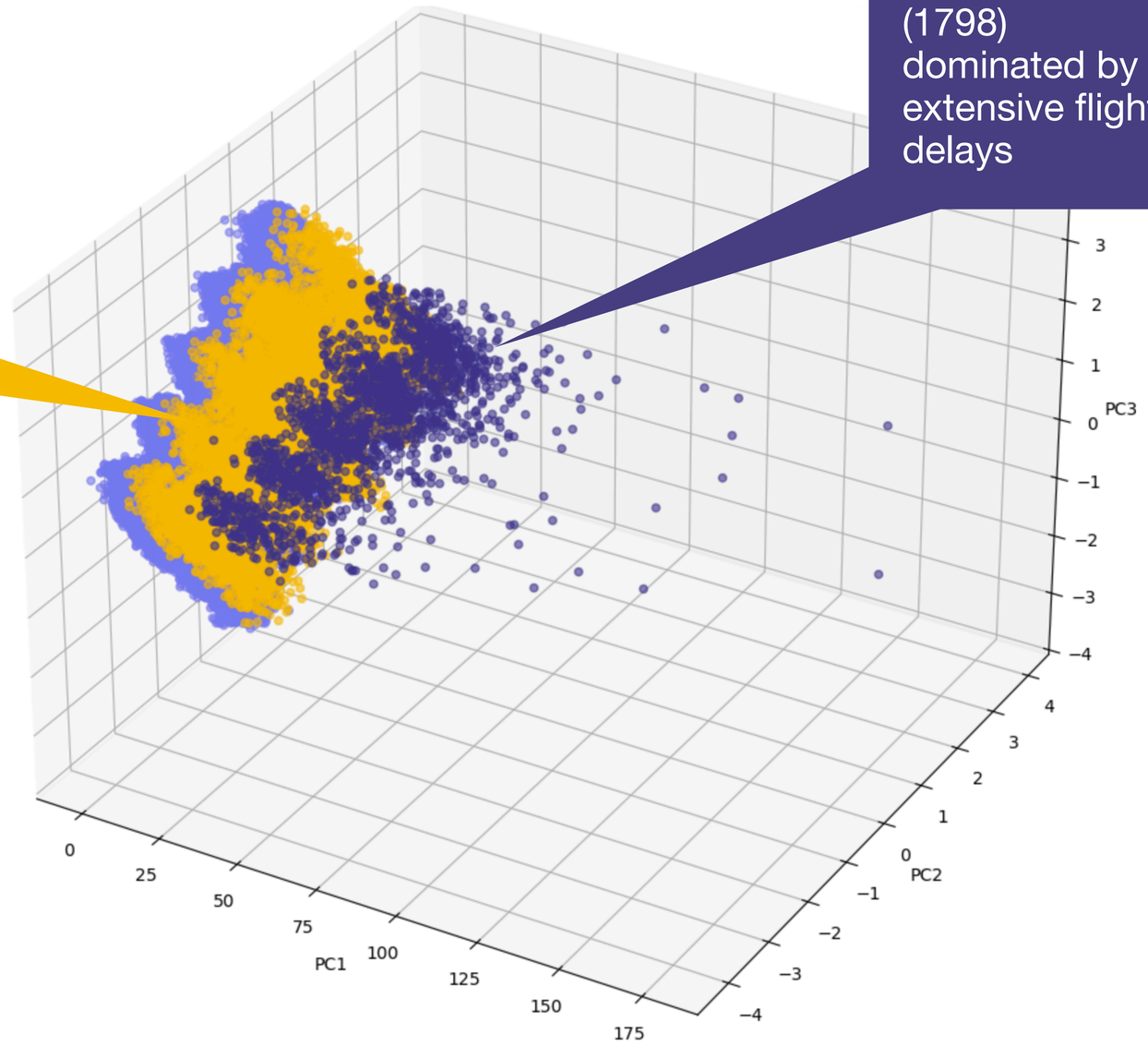

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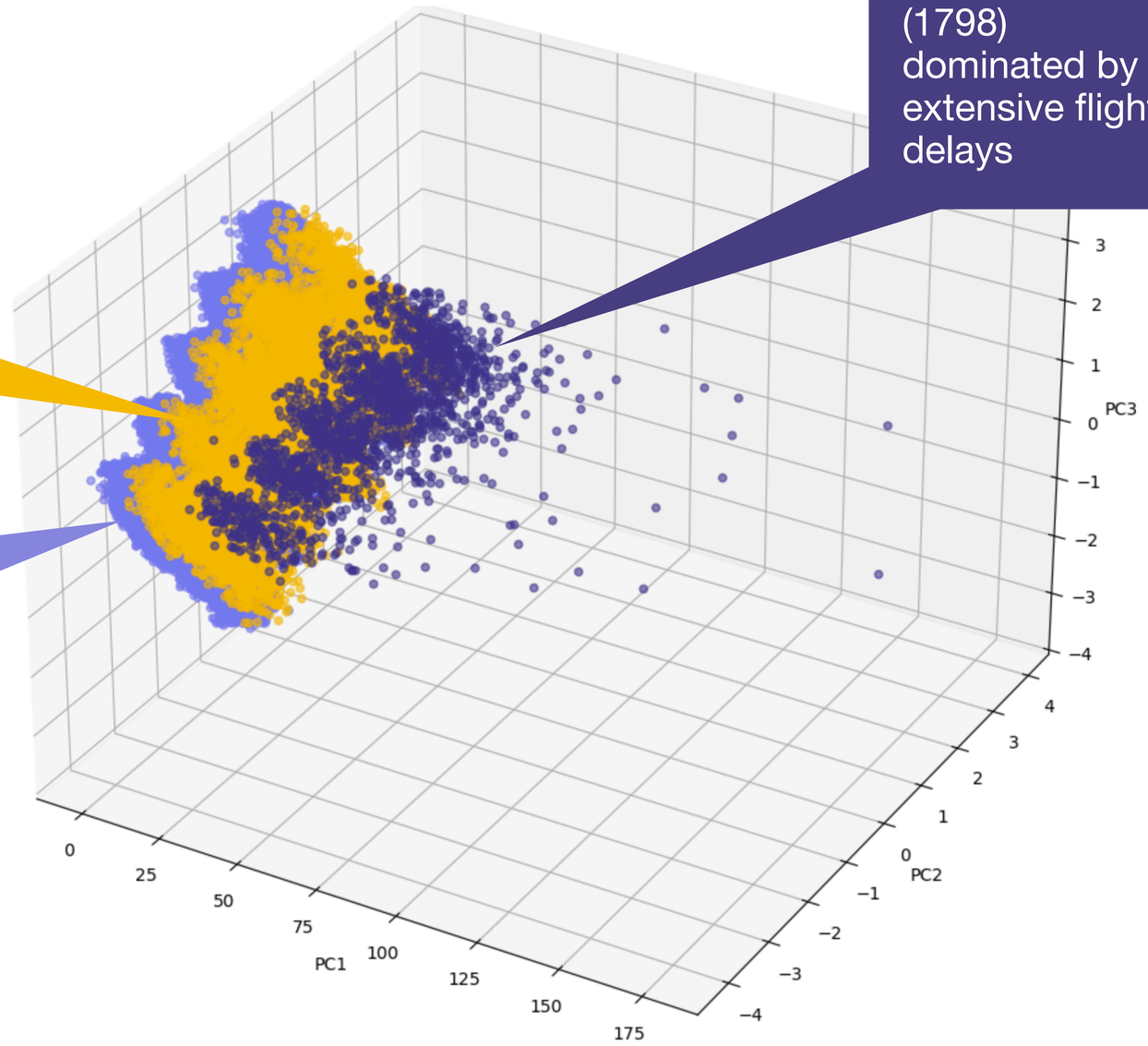

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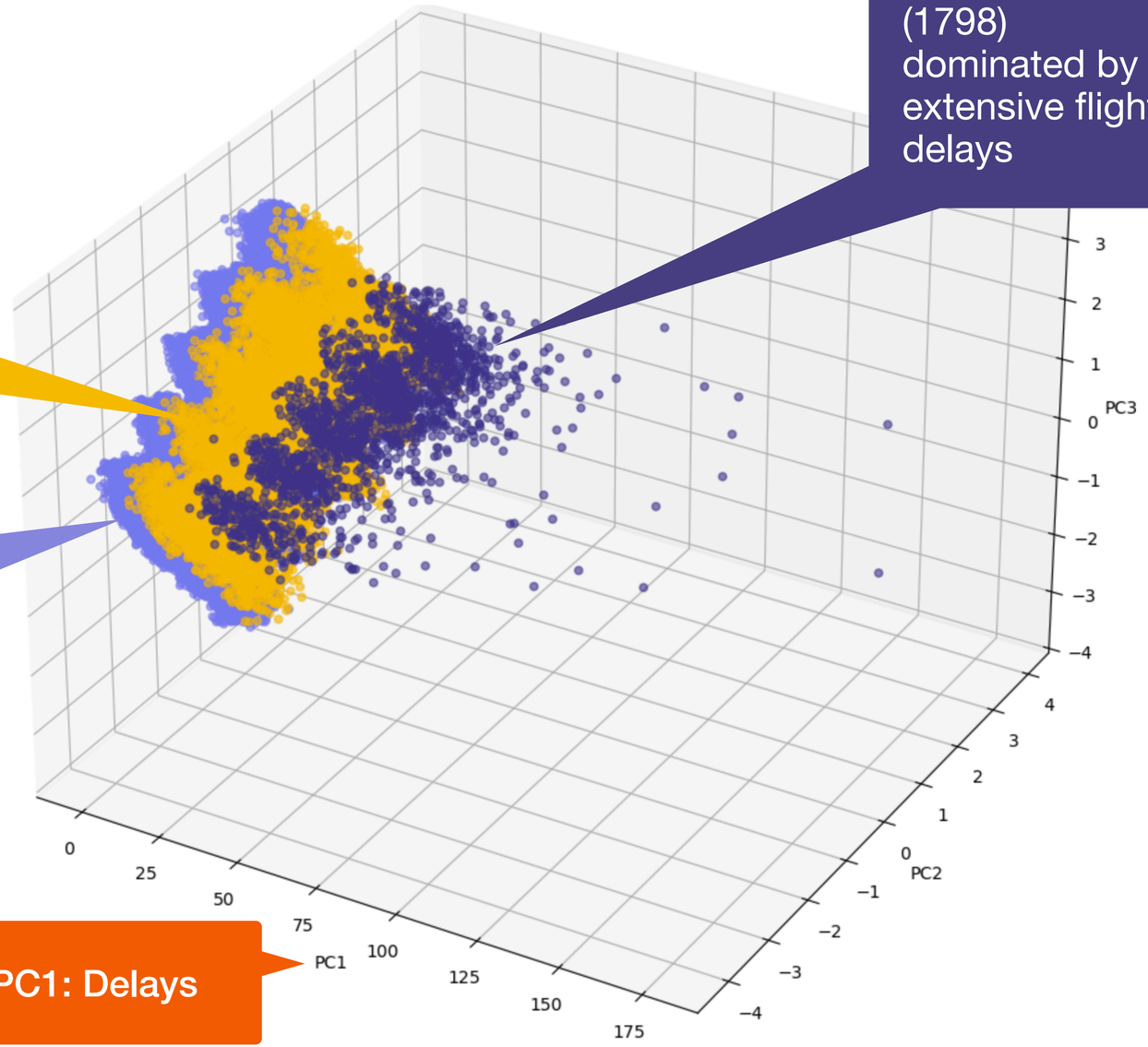

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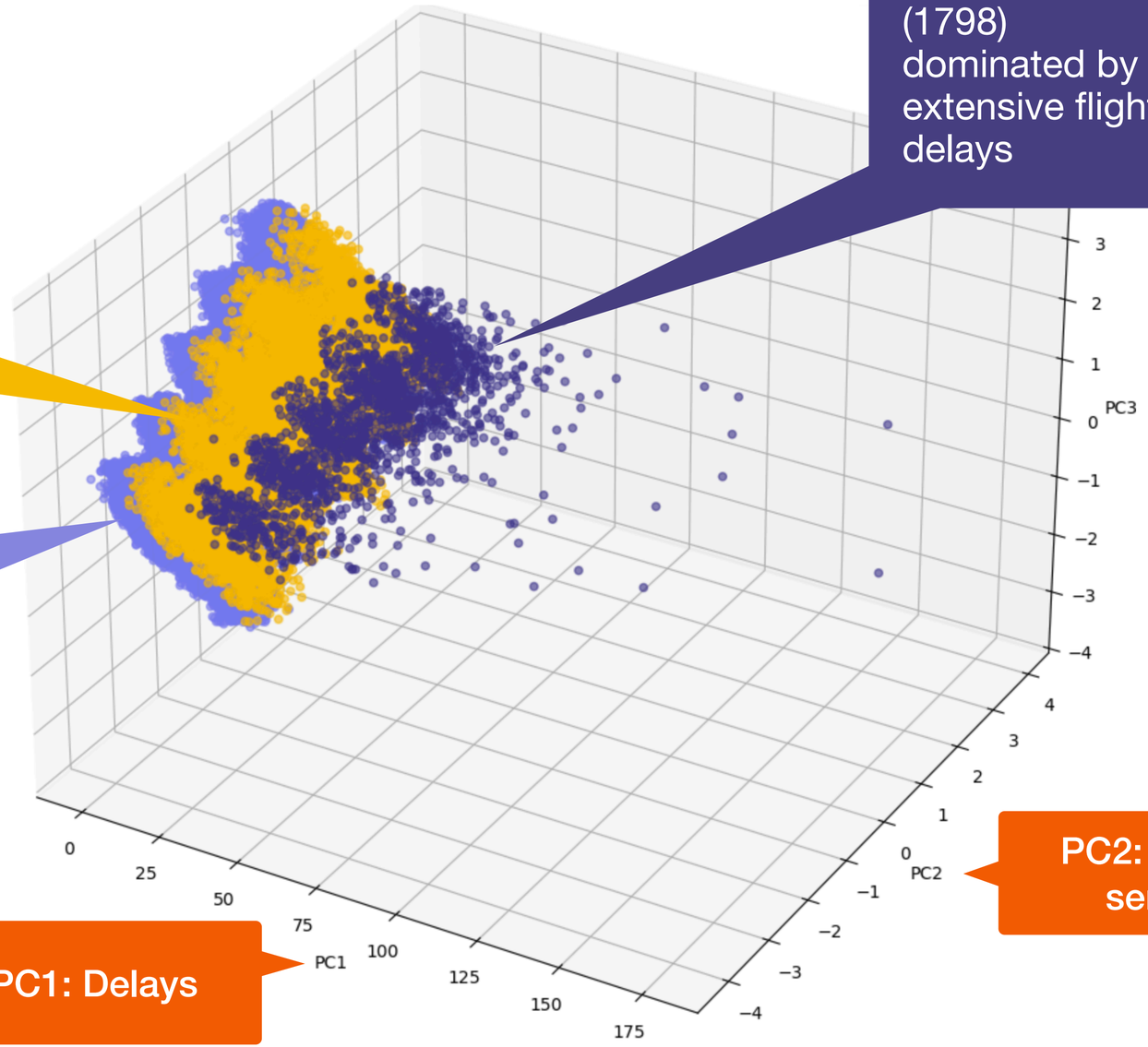

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PC1: Delays

PC2: Overall service

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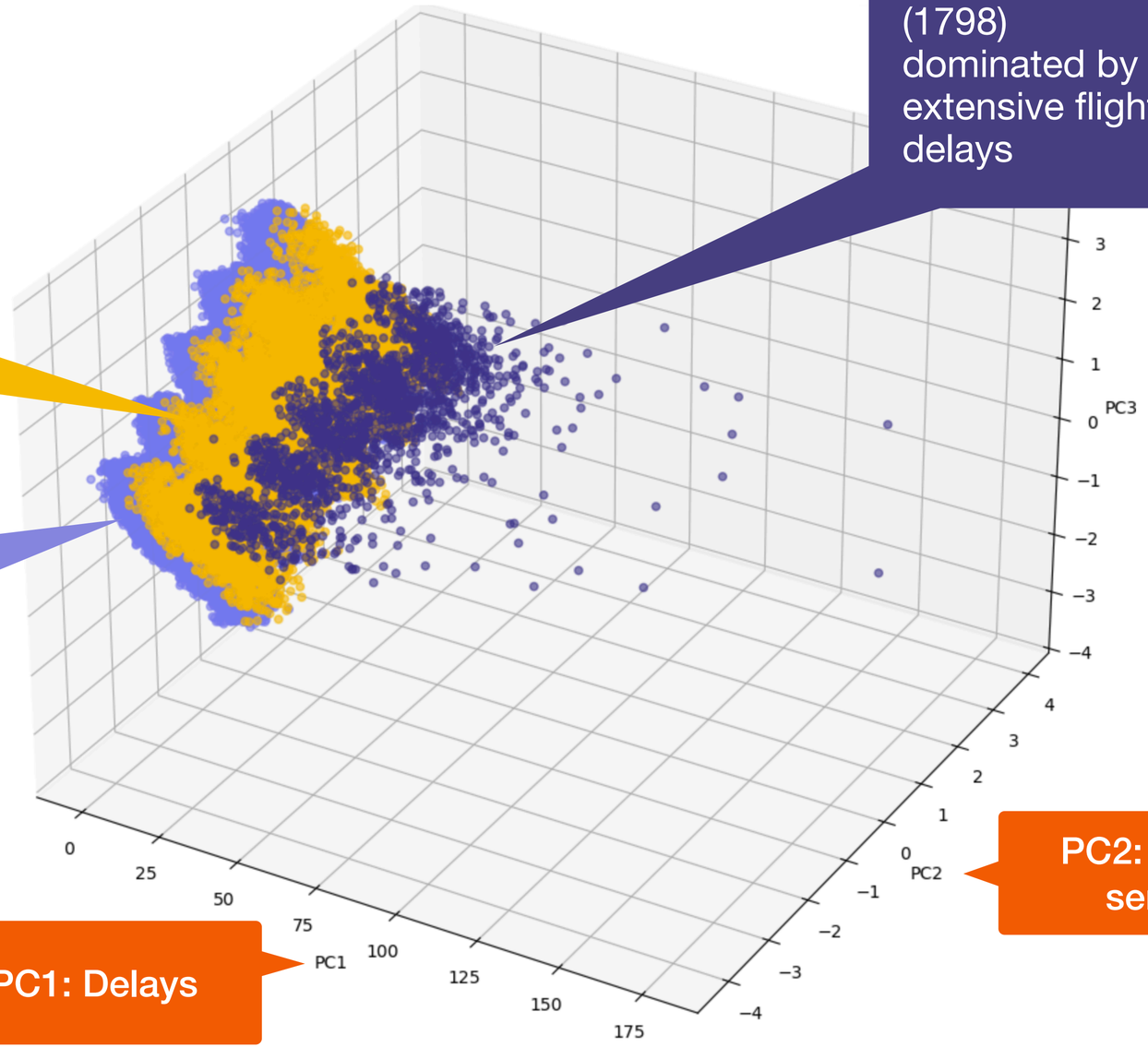

PC3: Tech & comfort

PC2: Overall service

PC1: Delays

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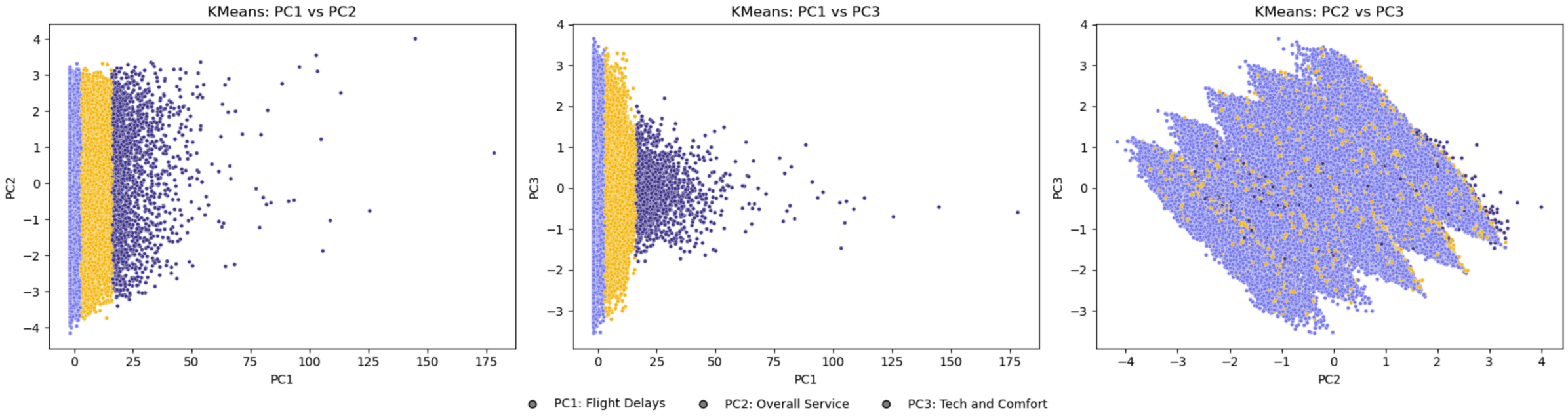

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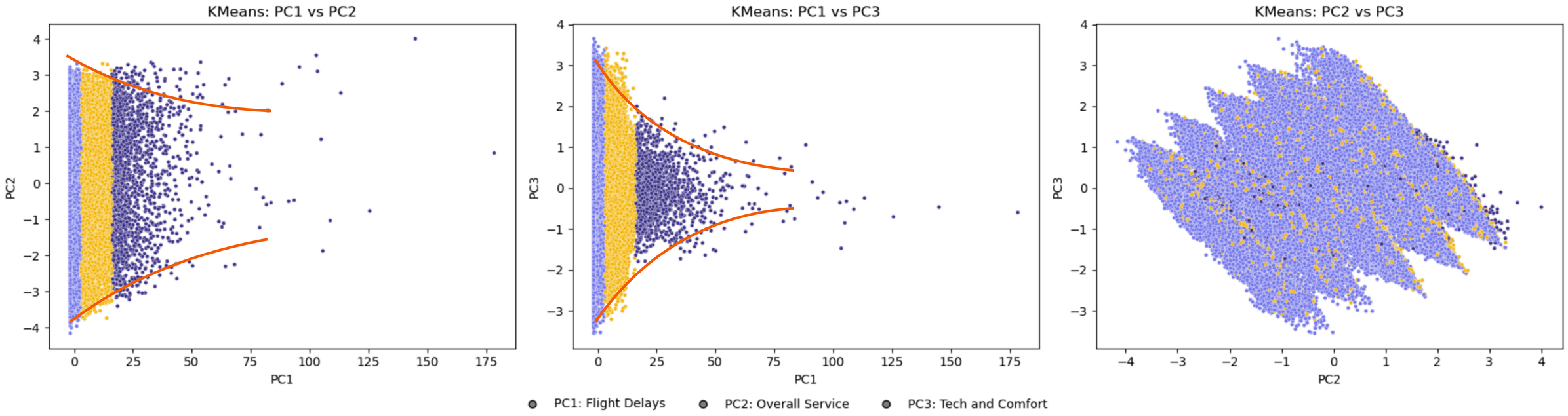

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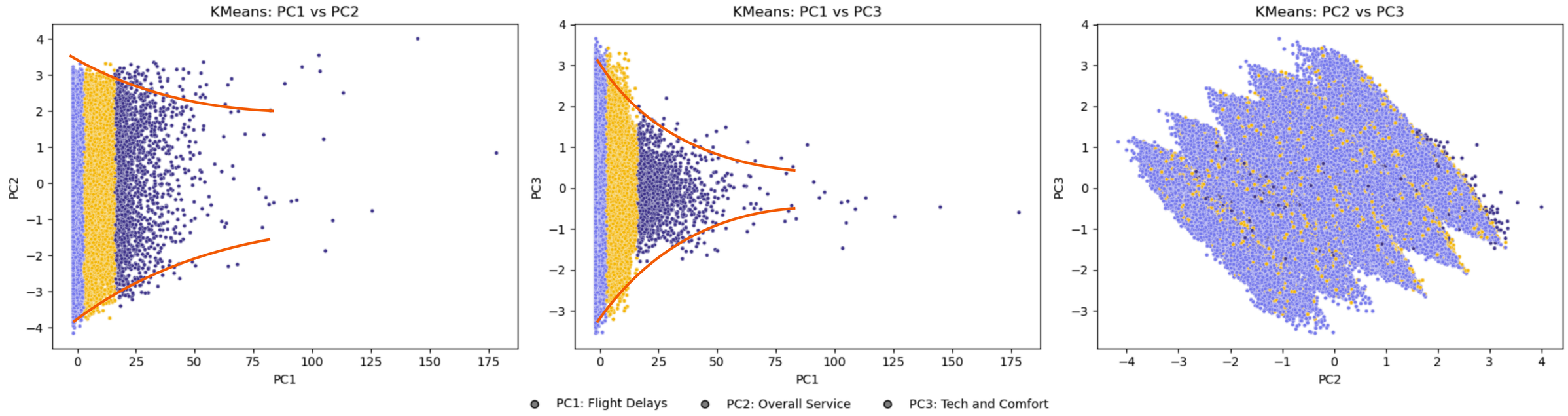

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- very satisfied → good flight + good service = delighted.
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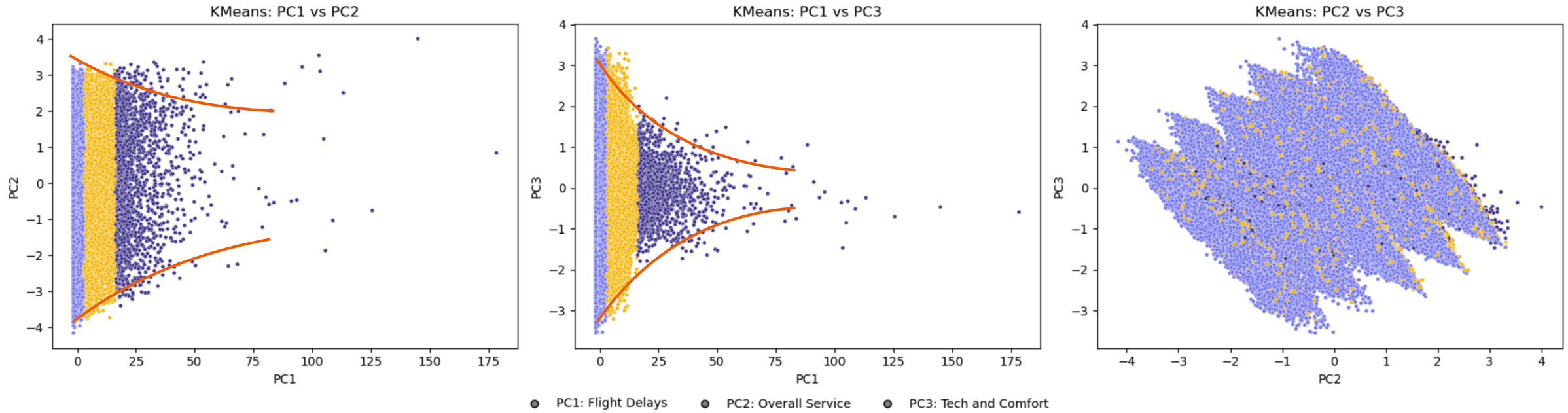

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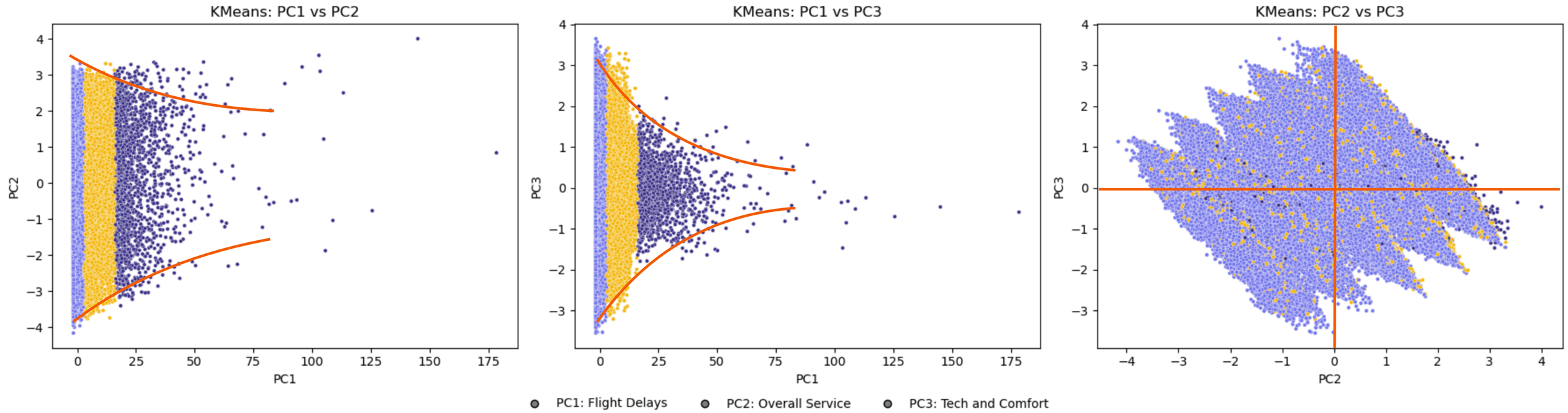

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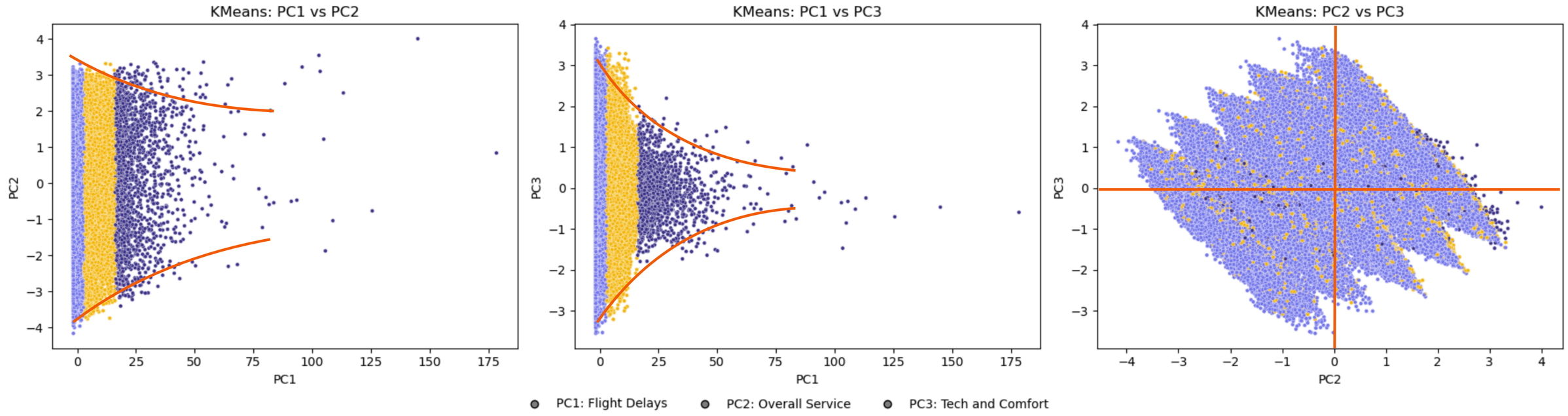

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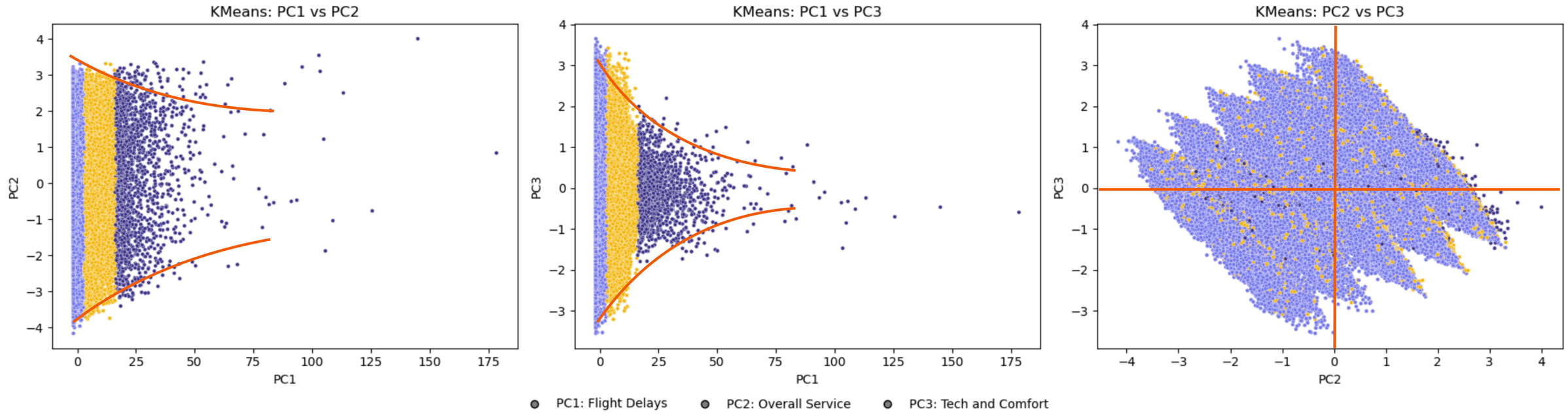

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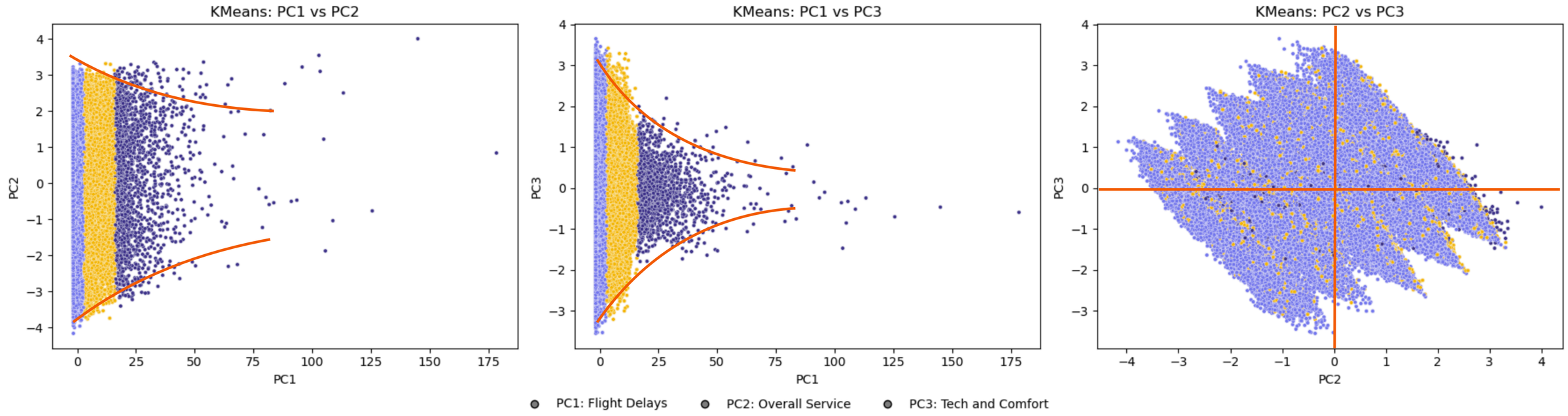

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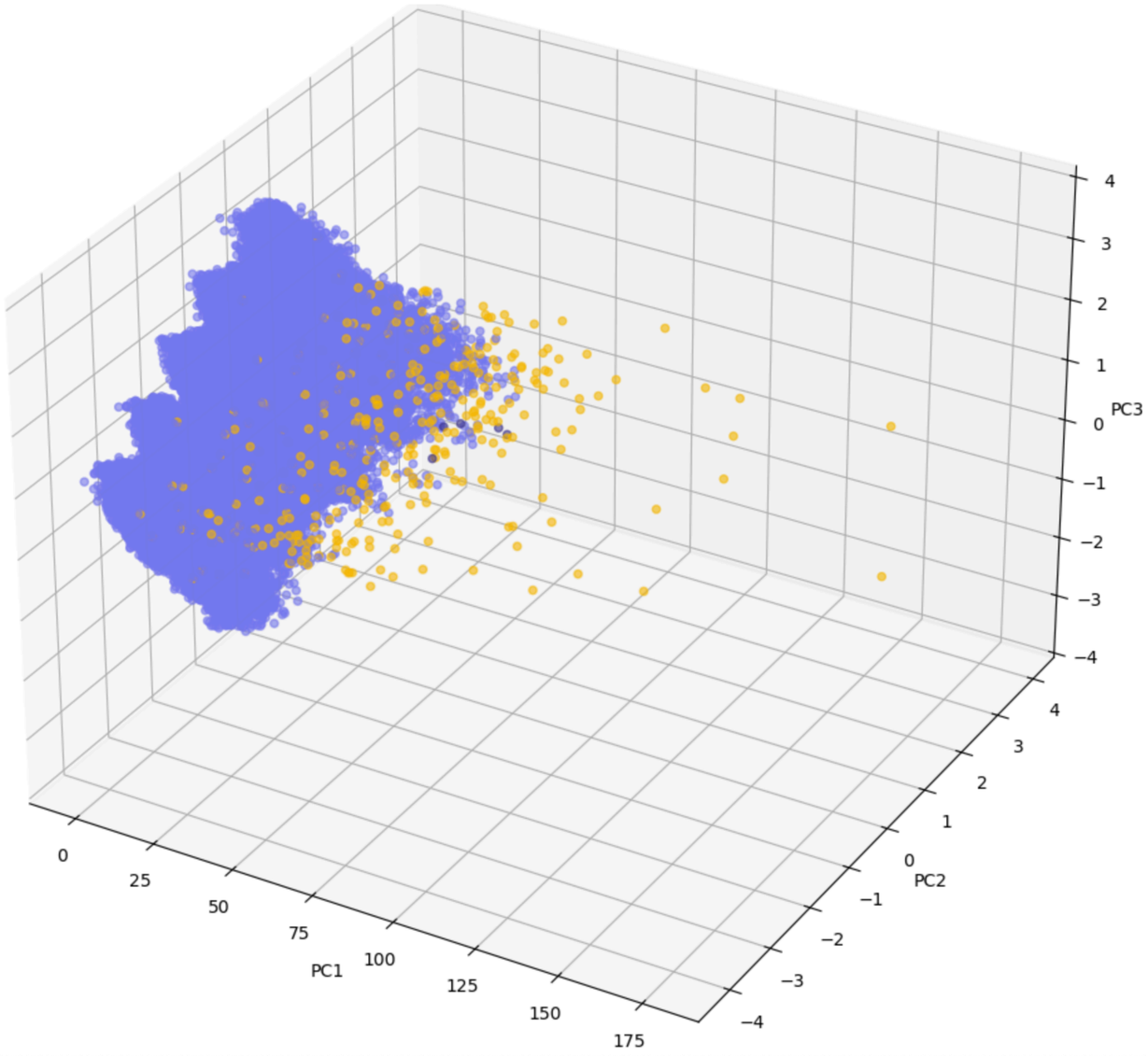

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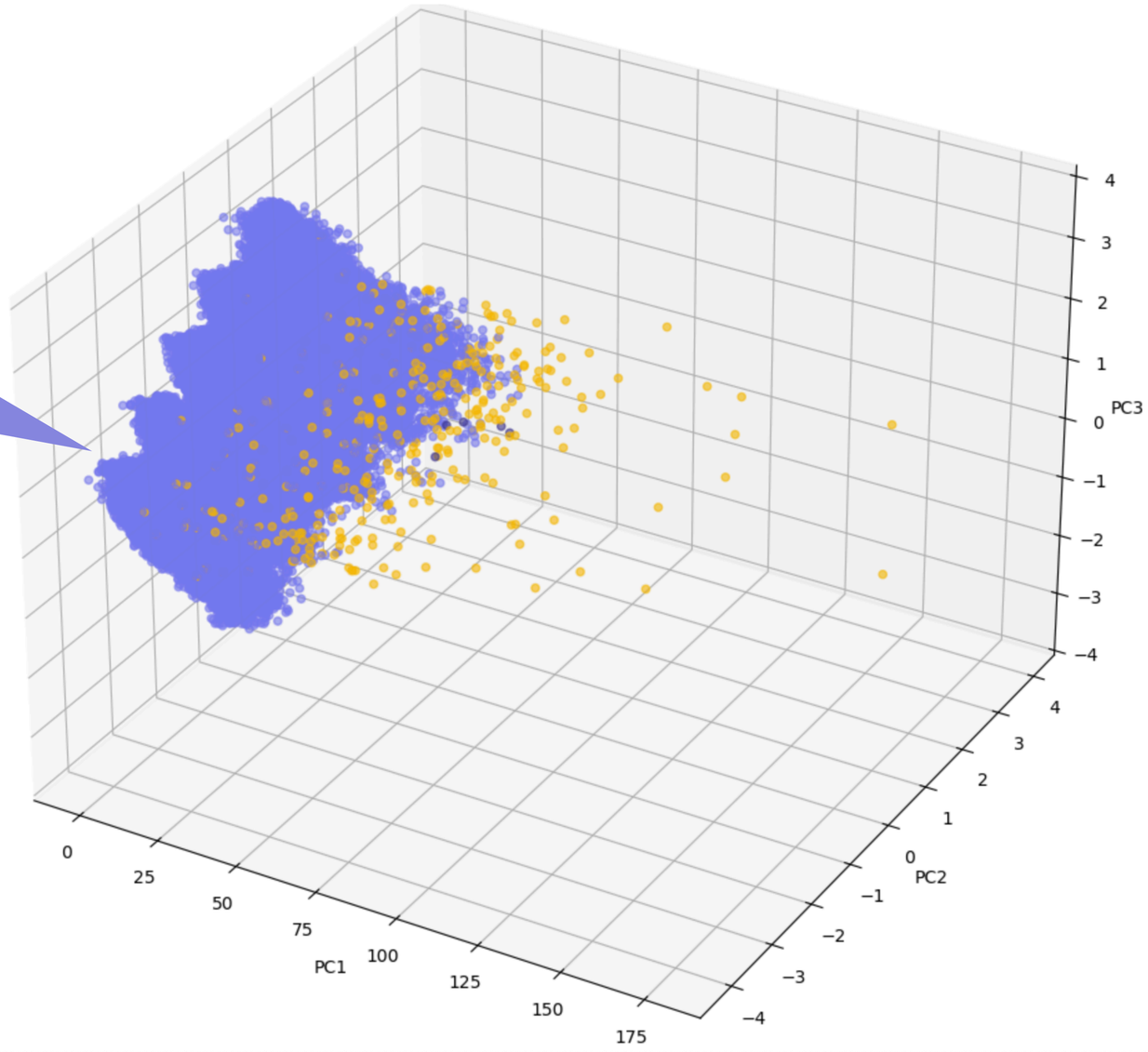
Not interpretable



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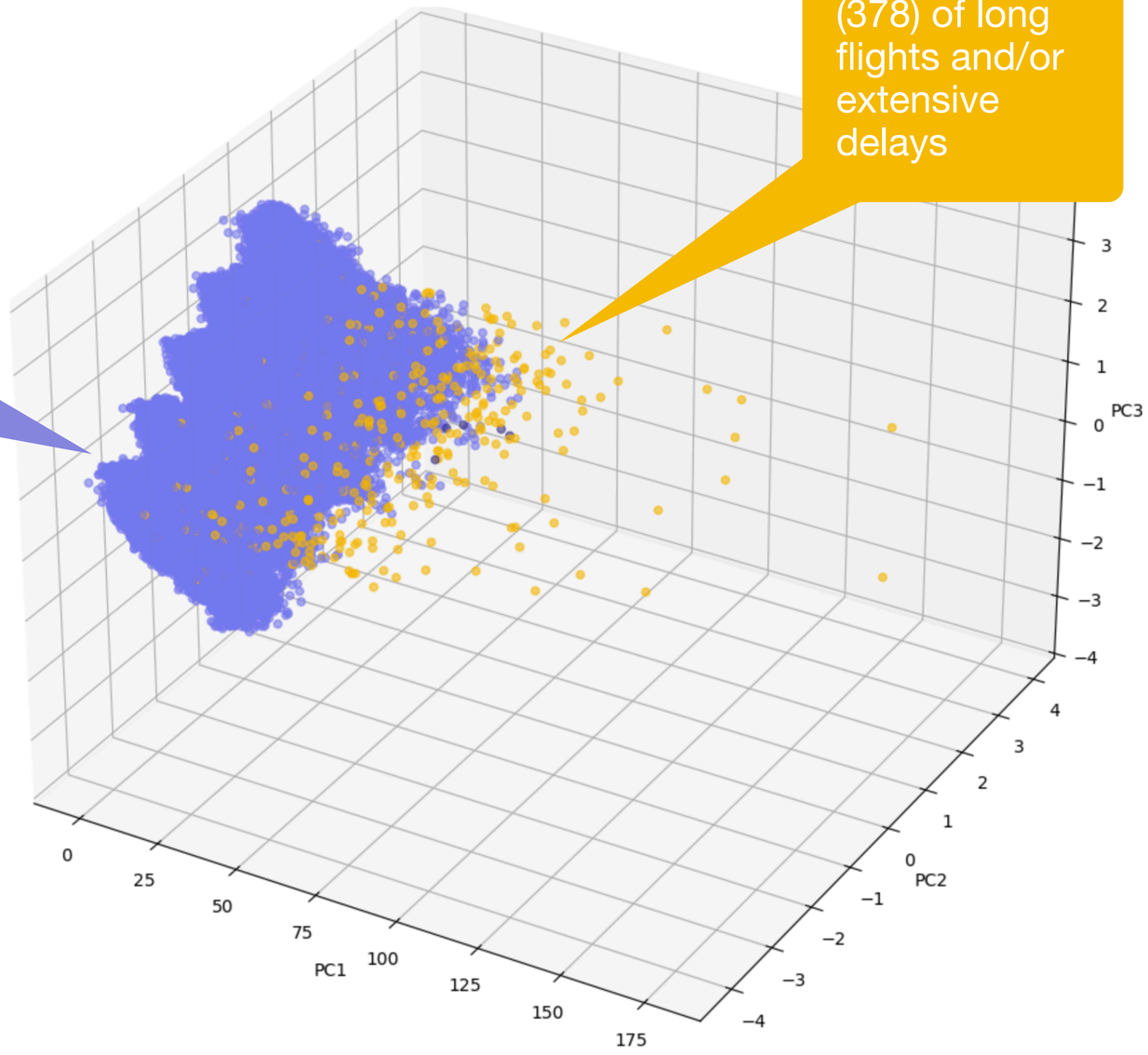
Noise/outliers (378) of long flights and/or extensive delays



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Target customer segments with tailored strategies (i.e. ticket discounts for first time travellers, comfort upgrades for returning customers, free wifi for business passengers)

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  - Examine correlation heat-maps of service-related features within each cluster.
  - Identify which customer types (i.e. business vs. personal, returning vs. new) are most dominant in each cluster.
  - Analyse the cluster centroids to uncover deeper insights about the typical passenger in each group.

- Repeat the analysis after removing the delay features to see if other underlying patterns become more evident.
- Explore soft clustering techniques:
  - Gaussian Mixture Models (GMM): assign each passenger a probability of belonging to each cluster, rather than forcing a hard assignment.

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- Explore soft clustering techniques:
  - Gaussian Mixture Models (GMM): assign each passenger a probability of belonging to each cluster, rather than forcing a hard assignment.
  - Soft clustering is particularly useful when clusters overlap or boundaries are unclear.

Questions ?