



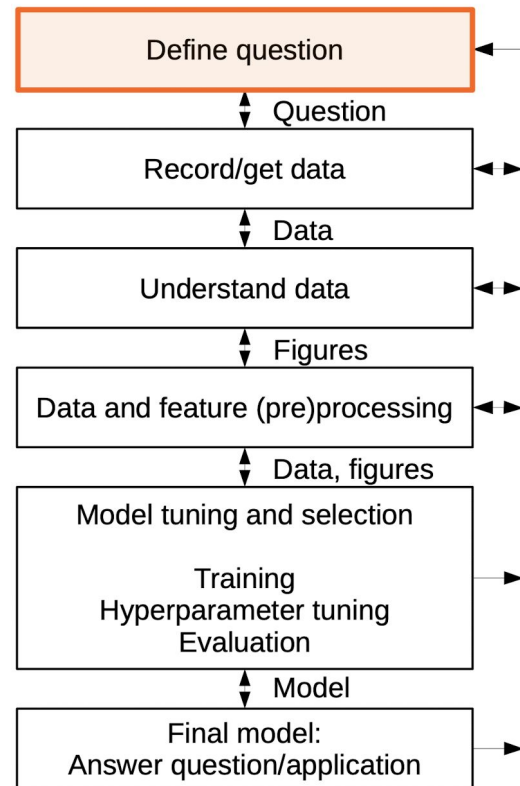
# Name That Genre

**Spotify Genre Classification Using Machine Learning**

Ciesla, Hörschinger, Oberascher

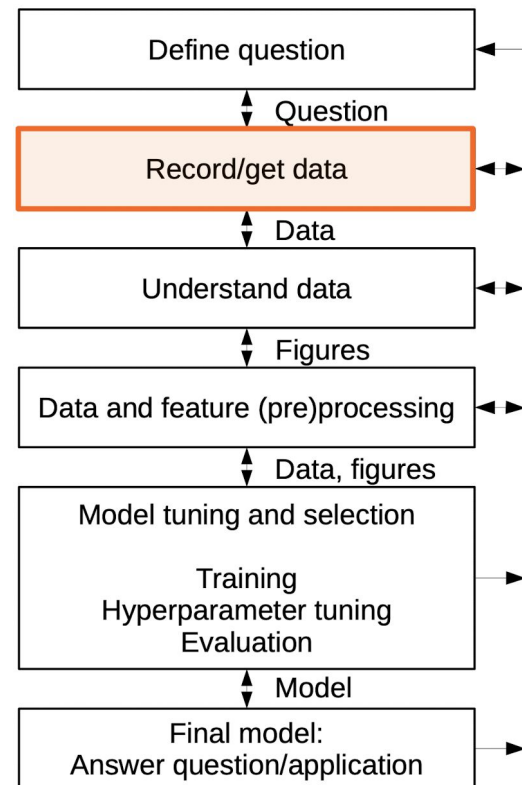
## Define question and goal

- Predict Genre of Songs
- Evaluate Performances of different ML models

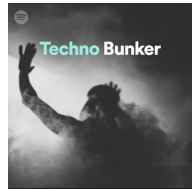


## Record Data - Overview

- \$ pip install *spotipy*
- create spotify developer account
- `playlist_items(playlist_id)` -> get all track IDs from playlist
- `audio_features([track_ids])` -> get list of audio features from list of track IDs
- save features to .json file



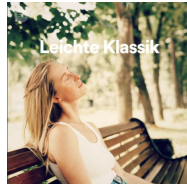
# Record Data - Labeling



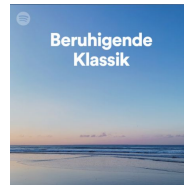
Main Stage



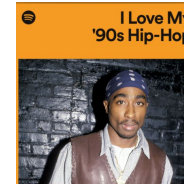
edm



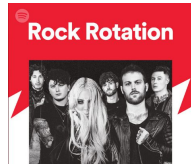
classic



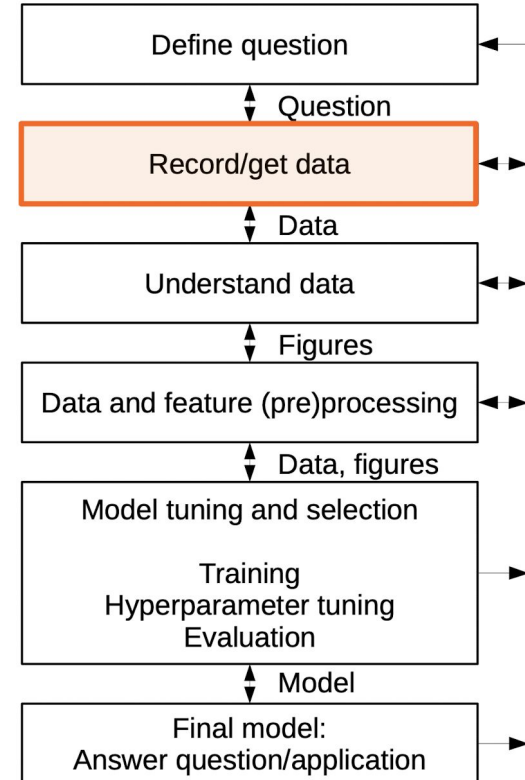
jazz



hiphop

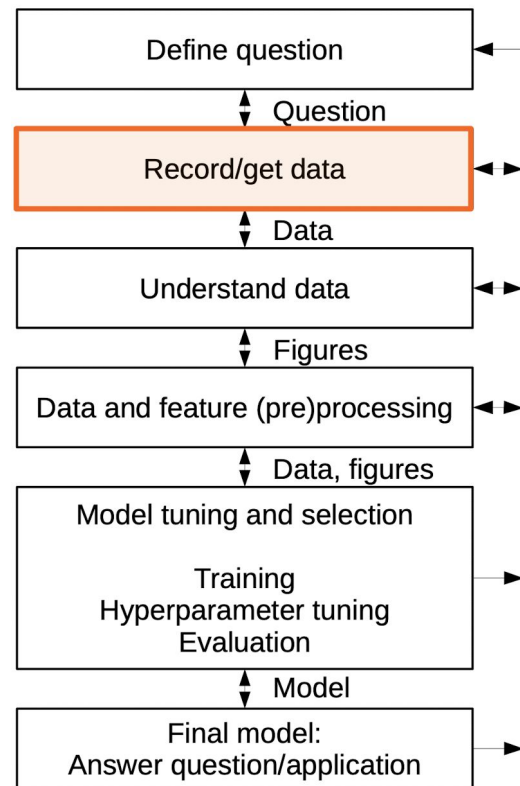


rock



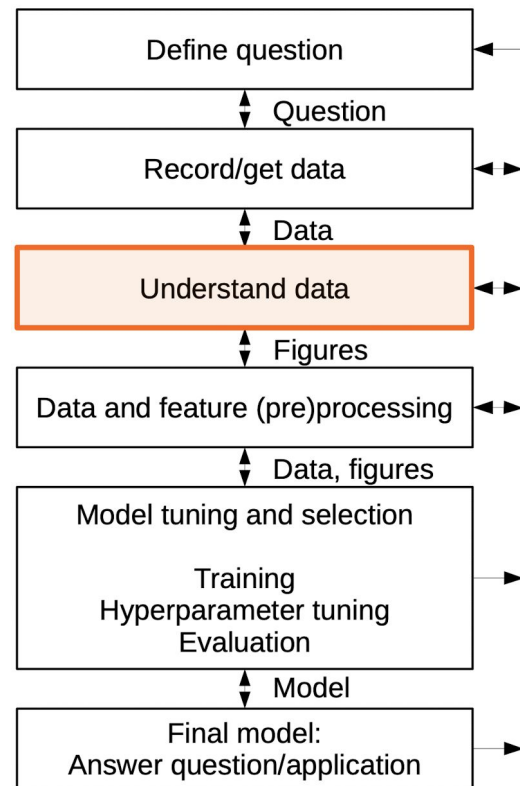
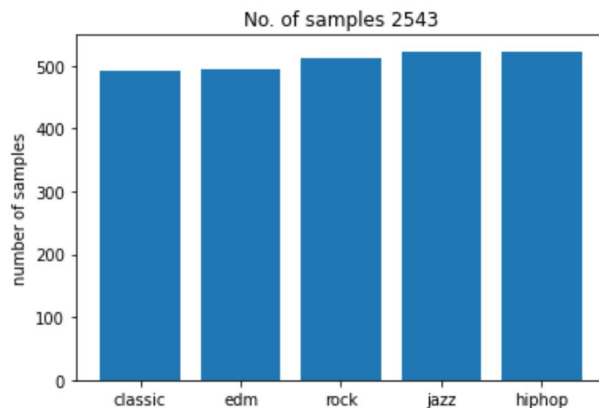
# Record Data - Audio Features

```
{
  "danceability":0.194,
  "energy":0.0324,
  "key":5,
  "loudness":-28.215,
  "mode":1,
  "speechiness":0.0382,
  "acousticness":0.982,
  "instrumentalness":0.961,
  "liveness":0.0916,
  "valence":0.0596,
  "tempo":144.13,
  "type":"audio_features",
  "id":"2YarjDYjBJuH63dUIh90Wv",
  "uri":"spotify:track:2YarjDYjBJuH63dUIh90Wv",
  "track_href":"https://api.spotify.com/v1/tracks/2YarjDYjBJuH63dUIh90Wv",
  "analysis_url":"https://api.spotify.com/v1/audio-analysis/2YarjDYjBJuH63dUIh90Wv",
  "duration_ms":433800,
  "time_signature":4,
  "genre":"classic",
  "playlist_id":"37i9dQZF1DXaHEllsiT8lf"
},
```

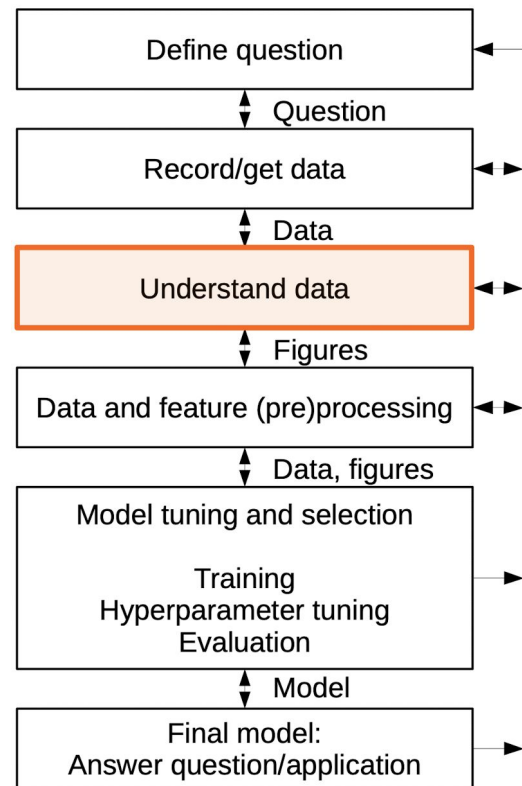
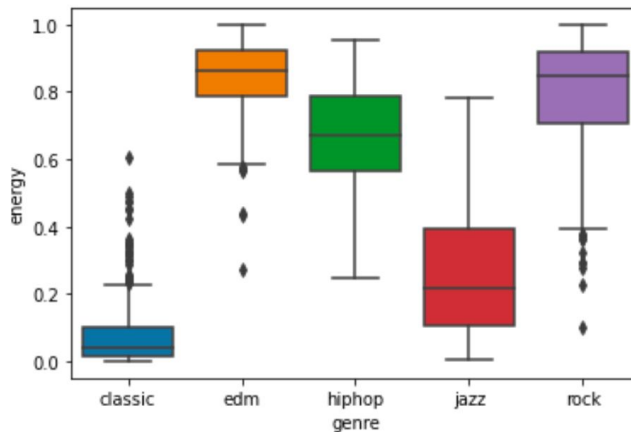
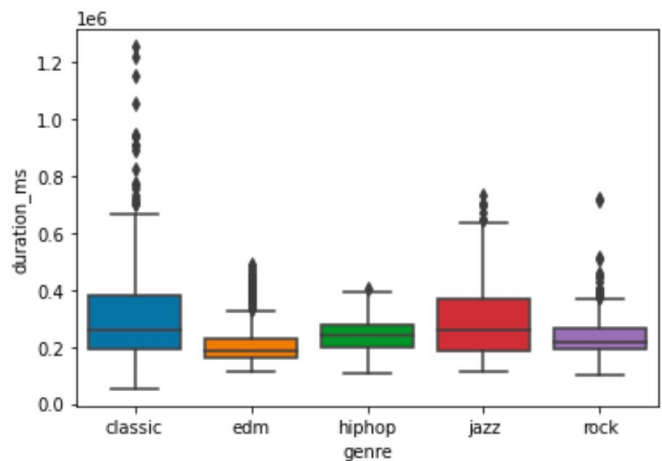


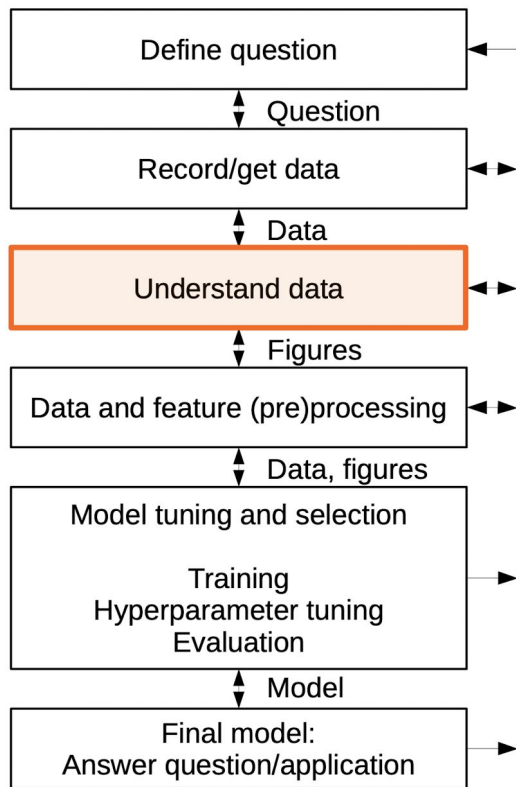
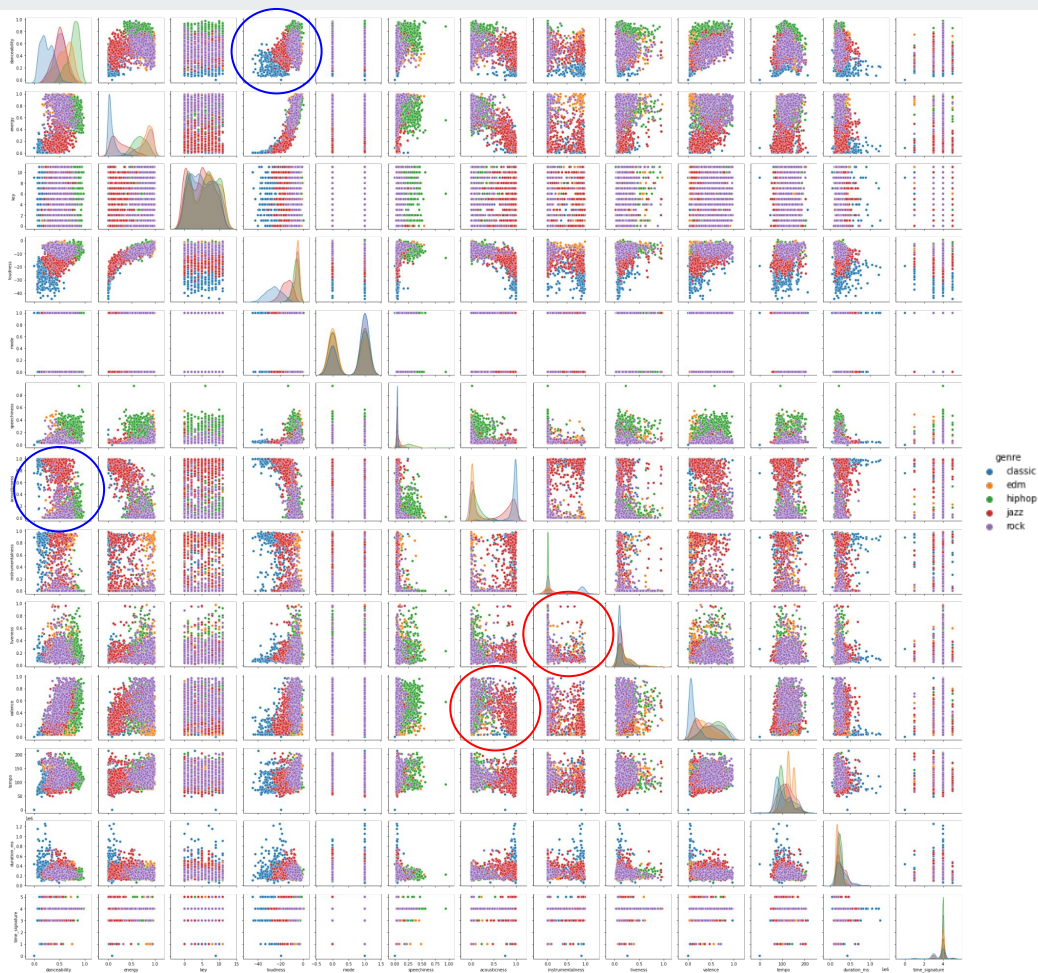
# Understand Data

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2580 entries, 0 to 2579
Data columns (total 15 columns):
#   Column          Non-Null Count  Dtype
---  ---
0   danceability     2580 non-null   float64
1   energy           2580 non-null   float64
2   key              2580 non-null   int64
3   loudness         2580 non-null   float64
4   mode             2580 non-null   int64
5   speechiness      2580 non-null   float64
6   acousticness     2580 non-null   float64
7   instrumentalness  2580 non-null   float64
8   liveness         2580 non-null   float64
9   valence          2580 non-null   float64
10  tempo            2580 non-null   float64
11  duration_ms      2580 non-null   int64
12  time_signature   2580 non-null   int64
13  genre            2580 non-null   object
14  playlist_id      2580 non-null   object
dtypes: float64(9), int64(4), object(2)
memory usage: 302.5+ KB
```

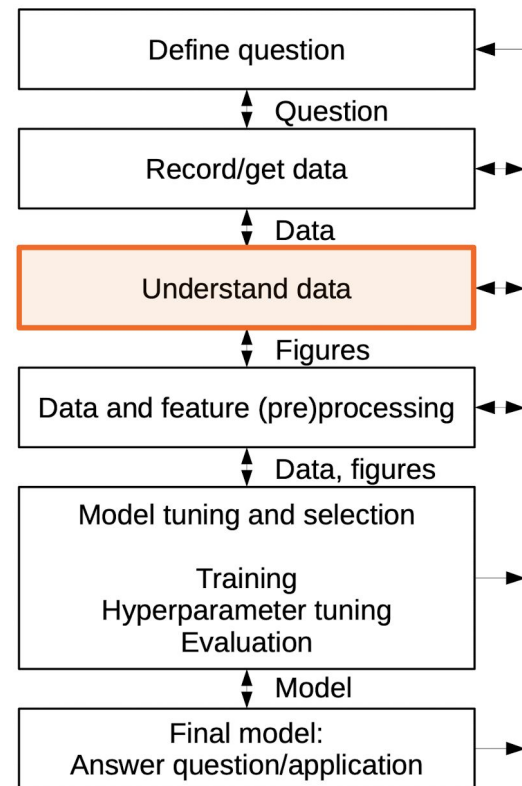
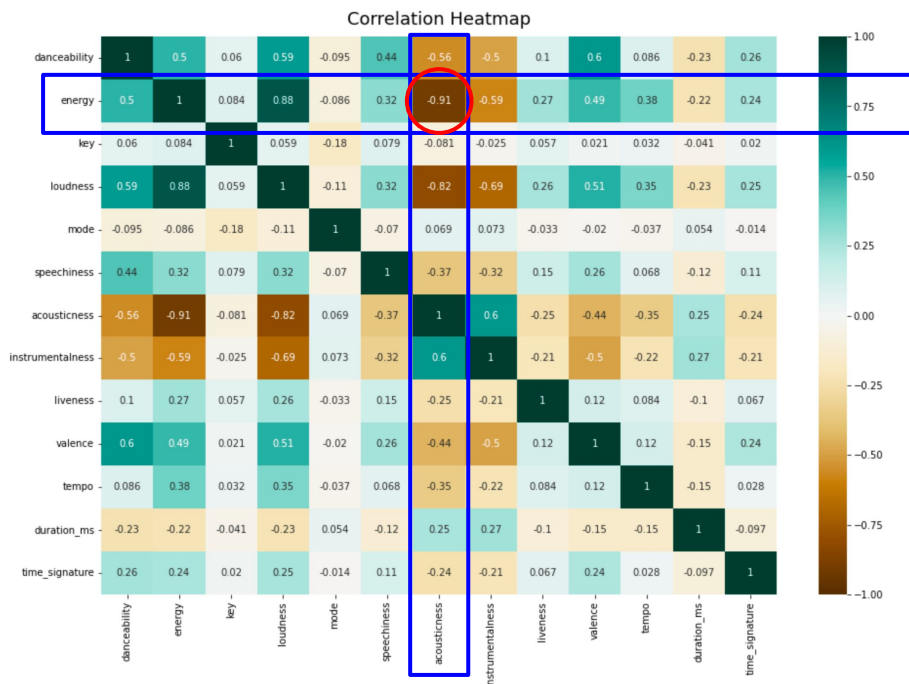


# Understand Data



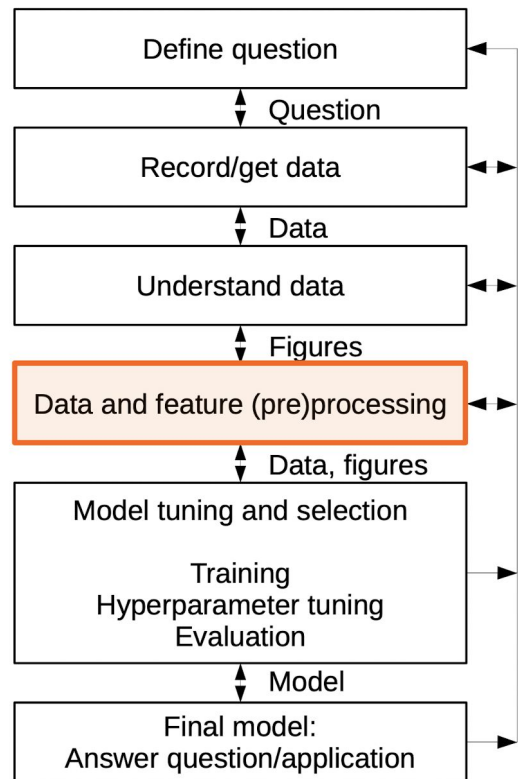






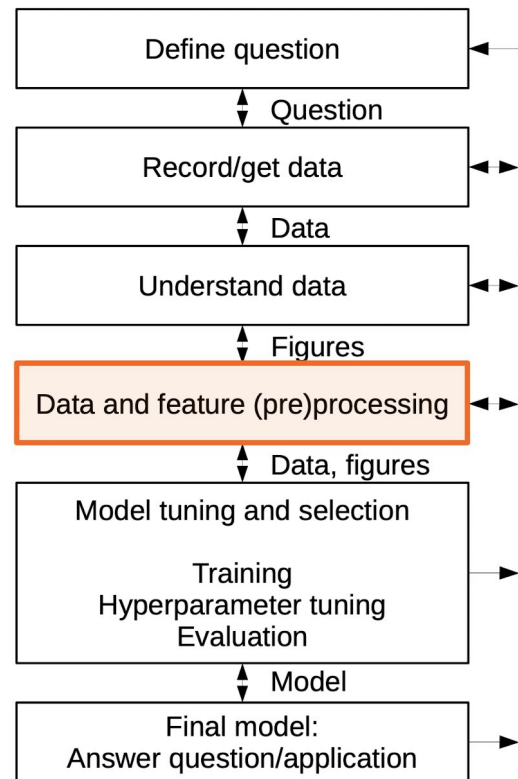
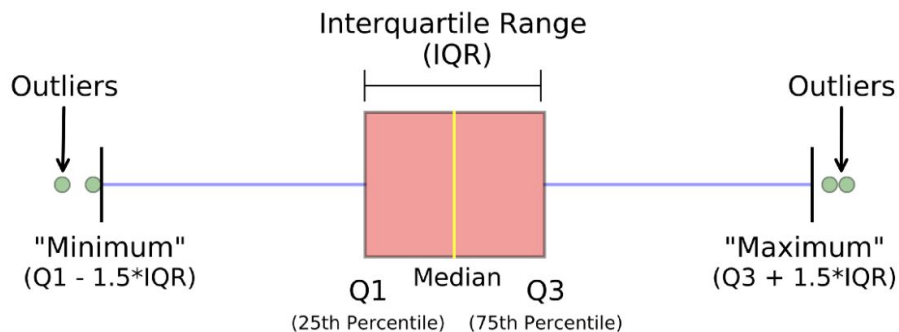
# Data and Feature Preprocessing

- Remove invalid samples
  - some samples with wrong key and wrong time signature
  - `key == -1` or `time_signature` not in `[3,7]`
- Reduce highly correlated features
  - energy & loudness
- Scale numerical features to mean = 0 & standard deviation = 1



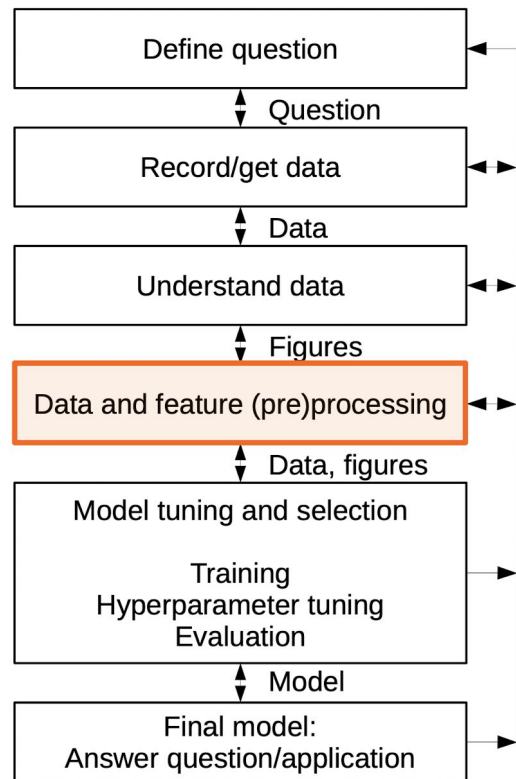
# Data and Feature Preprocessing

- Restrict outliers
  - upper whisker  $\rightarrow Q3 + 1.5 \cdot IQR$
  - lower whisker  $\rightarrow Q1 - 1.5 \cdot IQR$

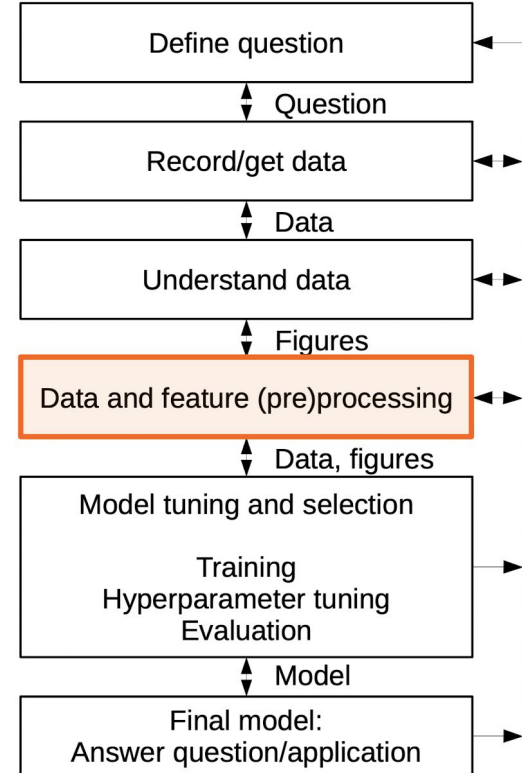
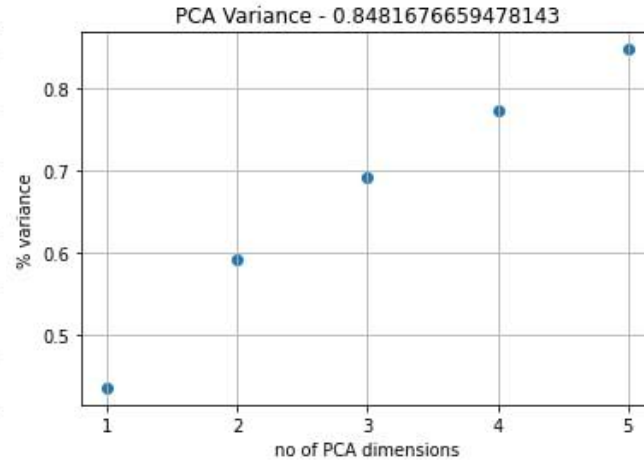
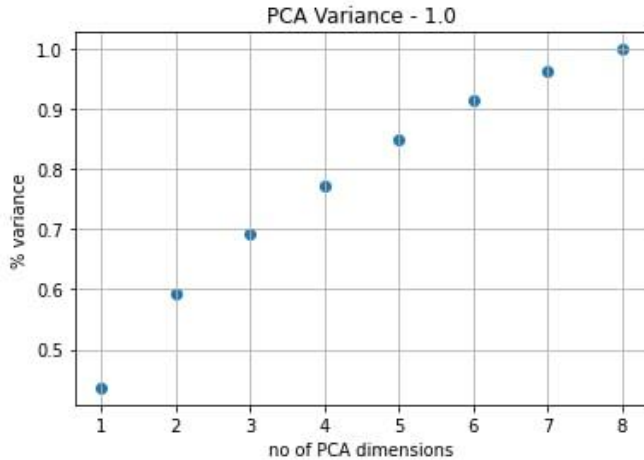


# Data and Feature Preprocessing

- One-hot-encoding for categorical features
- **Final features**
  - numerical → danceability, speechiness, acousticness, instrumentalness, liveness, valence, tempo, duration\_ms
  - categorical → mode (binary), time\_signature\_0 - time\_signature\_5, key\_0 - key\_11
- Perform preprocessing steps on training set
- Perform **same** preprocessing steps on test set

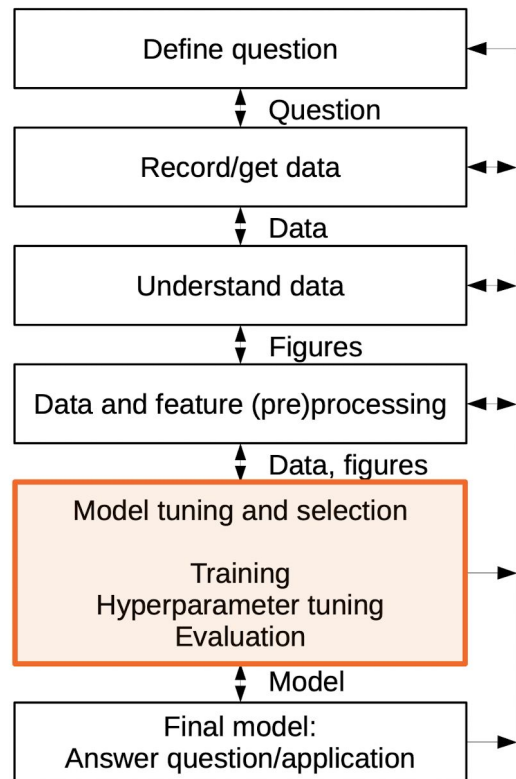


# Data and Feature Preprocessing - PCA



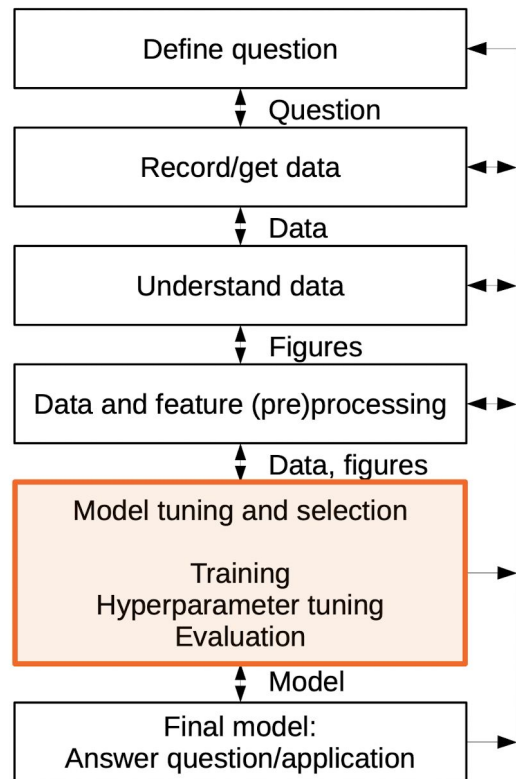
# Model tuning

- Nested Cross Validation
  - different data for hyperparameter tuning and model performance evaluation
  - for every estimator (KNN, SVC & Random Forest)
    - inner loop
      - 5-fold CV
      - grid search for hyperparameter tuning
    - outer loop → model performance evaluation
      - 5-fold CV



# Model selection

	model	params	nested_cv_training_acc	cv_training_acc	test_acc	test_roc_auc
0	knn	{"metric": "manhattan", "n_neighbors": 23, "we...	0.878553	0.857364	0.852713	0.980116
1	knn	{"metric": "euclidean", "n_neighbors": 26, "we...	0.842377	0.852196	0.855814	0.979187
2	knn	{"metric": "manhattan", "n_neighbors": 33, "we...	0.860465	0.859432	0.855814	0.981063
3	knn	{"metric": "manhattan", "n_neighbors": 16, "we...	0.832041	0.862016	0.854264	0.979672
4	knn	{"metric": "manhattan", "n_neighbors": 16, "we...	0.873385	0.862016	0.854264	0.979672
5	randomForest	{"max_depth": 40, "max_features": 5, "min_samp...	0.891473	0.893023	0.888372	0.987955
6	randomForest	{"max_depth": 30, "max_features": 5, "min_samp...	0.870801	0.896124	0.889922	0.988184
7	randomForest	{"max_depth": 30, "max_features": 5, "min_samp...	0.909561	0.888889	0.883721	0.987549
8	randomForest	{"max_depth": 60, "max_features": 5, "min_samp...	0.883721	0.895090	0.880620	0.987339
9	randomForest	{"max_depth": 30, "max_features": 10, "min_sam...	0.912145	0.893540	0.882171	0.987563
10	svc	{"C": 3.0, "gamma": 0.1, "kernel": "rbf"}	0.873385	0.869767	0.891473	0.983729
11	svc	{"C": 1.0, "gamma": 0.1, "kernel": "rbf"}	0.844961	0.864083	0.886822	0.982449
12	svc	{"C": 3.0, "gamma": 0.1, "kernel": "rbf"}	0.886305	0.869767	0.891473	0.983664
13	svc	{"C": 3.0, "gamma": 0.1, "kernel": "rbf"}	0.847545	0.869767	0.891473	0.983746
14	svc	{"C": 9.0, "gamma": 0.1, "kernel": "rbf"}	0.894057	0.870801	0.896124	0.984762

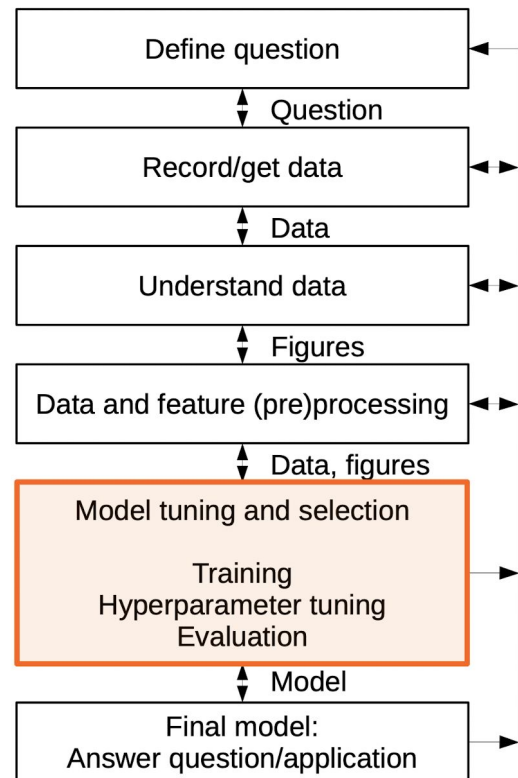
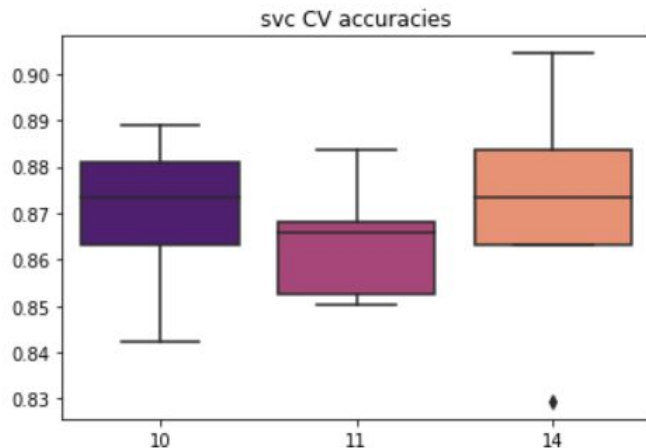


## Model selection - SVC

10: {"C": 3.0, "gamma": 0.1, "kernel": "rbf"}

11: {"C": 1.0, "gamma": 0.1, "kernel": "rbf"}

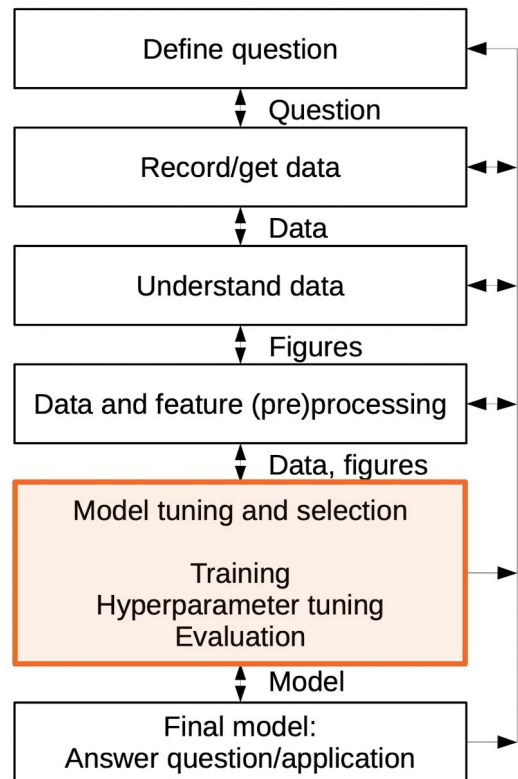
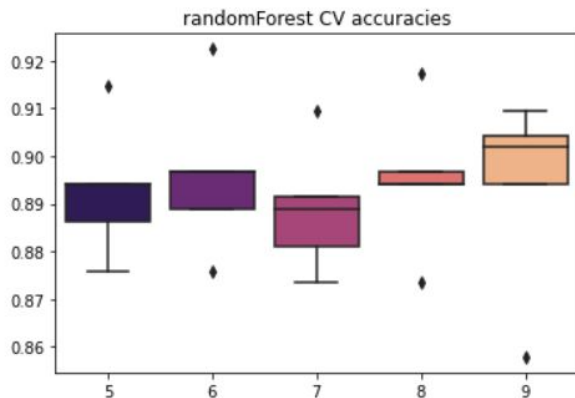
14: {"C": 9.0, "gamma": 0.1, "kernel": "rbf"}





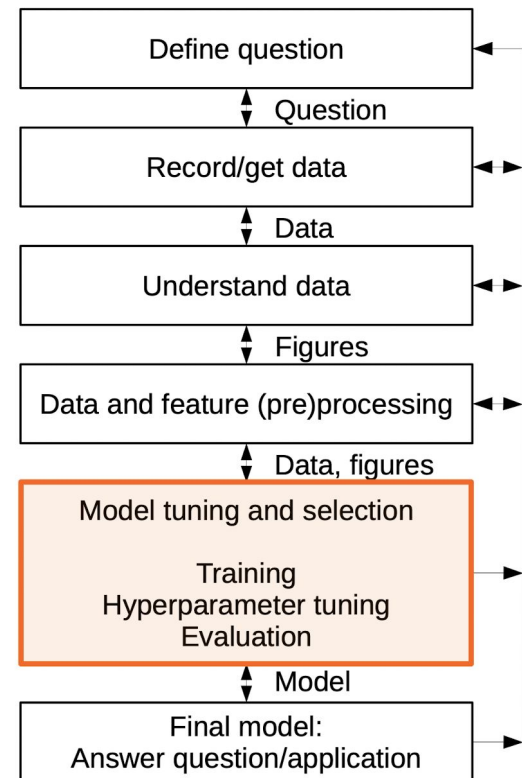
# Model selection - RF

5: {"max\_depth": 40, "max\_features": 5, "min\_samples\_leaf": 1, "min\_samples\_split": 5, "n\_estimators": 2000}  
6: {"max\_depth": 30, "max\_features": 5, "min\_samples\_leaf": 1, "min\_samples\_split": 3, "n\_estimators": 4000}  
7: {"max\_depth": 30, "max\_features": 5, "min\_samples\_leaf": 2, "min\_samples\_split": 3, "n\_estimators": 4000}  
**8: {"max\_depth": 60, "max\_features": 5, "min\_samples\_leaf": 2, "min\_samples\_split": 3, "n\_estimators": 1000}**  
9: {"max\_depth": 30, "max\_features": 10, "min\_samples\_leaf": 1, "min\_samples\_split": 3, "n\_estimators": 4000}

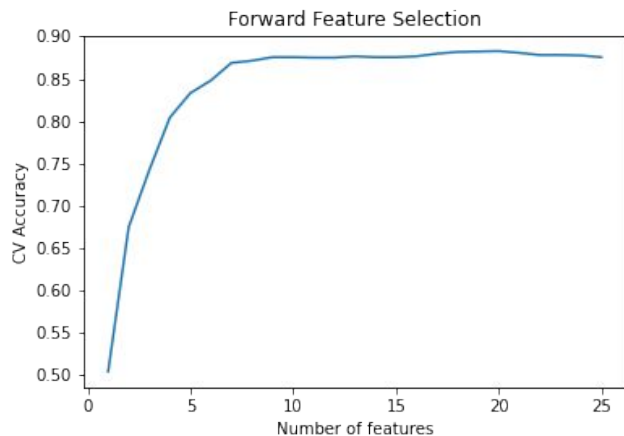


# Feature selection - Forward Selection

CV Accuracy	Nr.	Feature Names
0.504	1	acousticness
0.675	2	acousticness, danceability
0.742	3	acousticness, danceability, tempo
0.804	4	acousticness, danceability, tempo, valence
0.833	5	acousticness, danceability, tempo, valence, instrumentalness
0.848	6	acousticness, danceability, tempo, valence, instrumentalness, speechiness
0.869	7	acousticness, danceability, tempo, valence, instrumentalness, speechiness, duration_ms
0.871	8	acousticness, danceability, tempo, valence, instrumentalness, speechiness, duration_ms, key_4
0.875	9	acousticness, danceability, tempo, valence, instrumentalness, speechiness, duration_ms, key_4, key_11



# Feature selection - Forward Selection



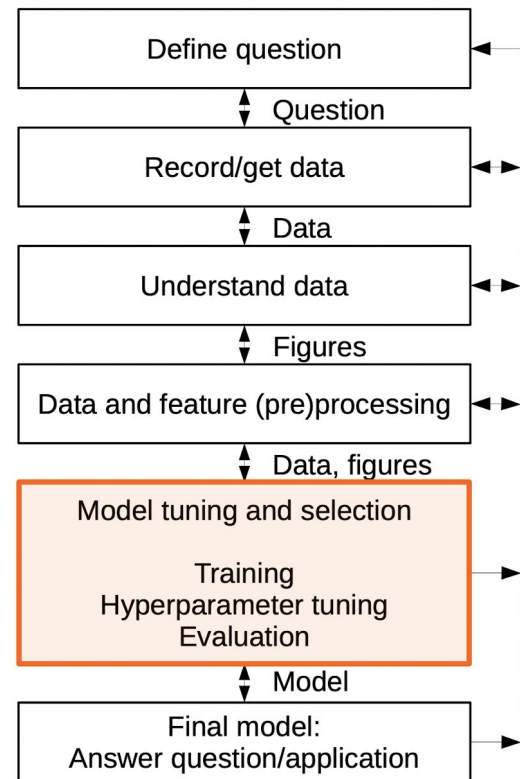
max = 0.883 (with 20 features)

SVC with Feature Selection

True label \ Predicted label	classic	edm	hiphop	jazz	rock
classic	121 18.76%	0 0.00%	0 0.00%	6 0.93%	0 0.00%
edm	0 0.00%	106 16.43%	8 1.24%	1 0.16%	10 1.55%
hiphop	0 0.00%	7 1.09%	121 18.76%	0 0.00%	3 0.47%
jazz	8 1.24%	3 0.47%	0 0.00%	119 18.45%	3 0.47%
rock	0 0.00%	19 2.95%	5 0.78%	5 0.78%	100 15.50%

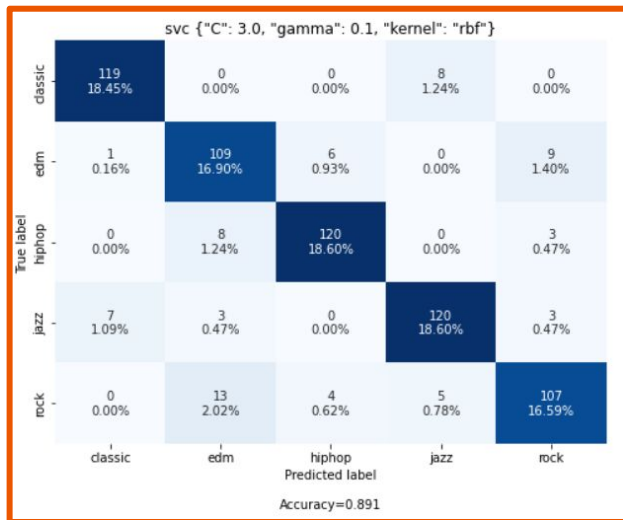
Accuracy=0.879

with 9 features

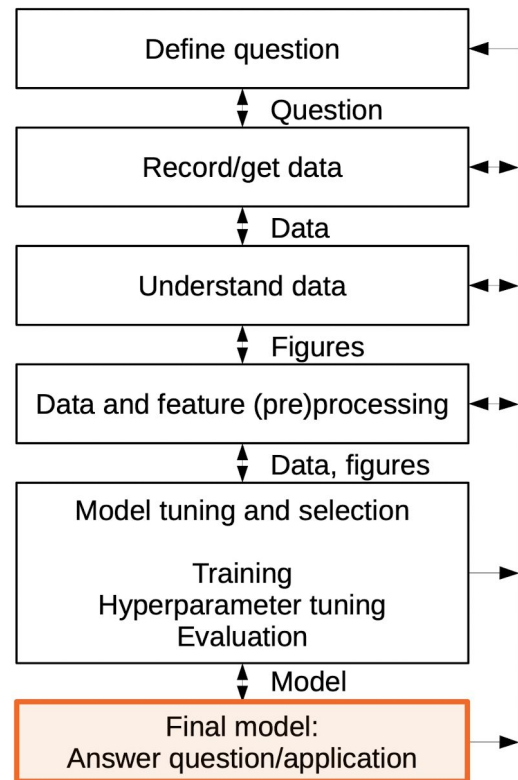
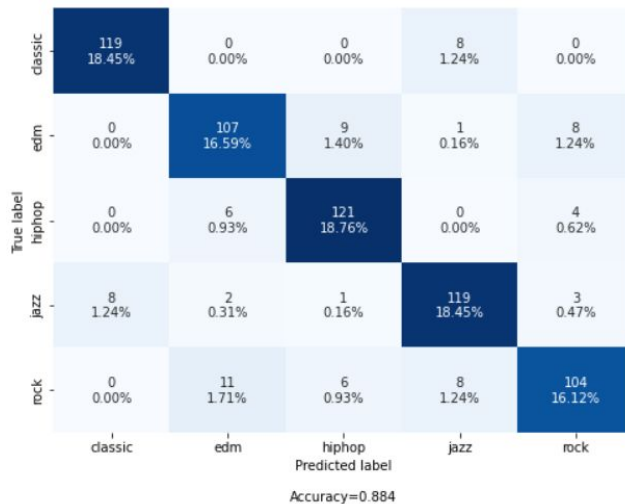


# Model selection → SVM

SVC



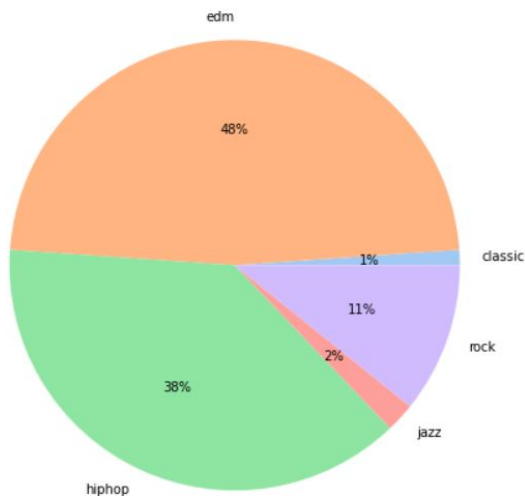
RF



# Final model - answer the question

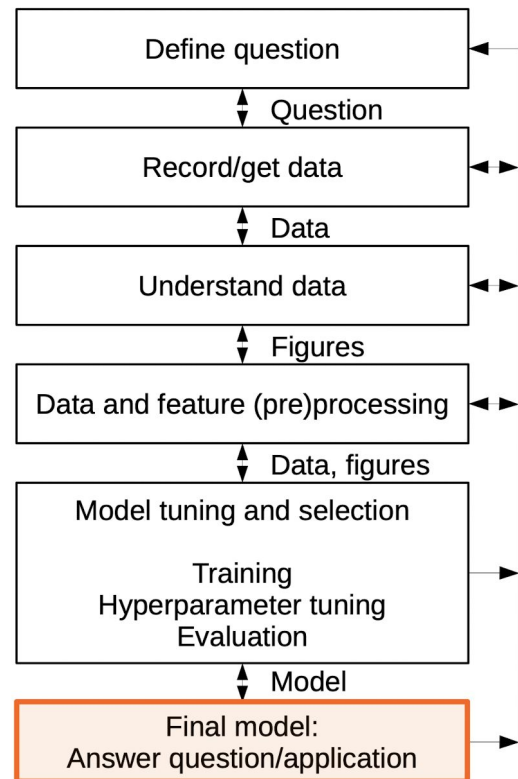
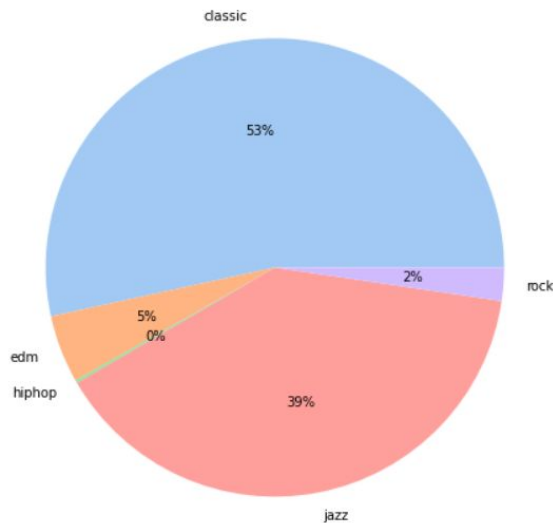
Lose Yourself - Eminem

hiphop → edm



Dear Kathy - Benny Golson

jazz → classic





**Thank you for your attention!**