MusicMood

Machine Learning in Automatic Music Mood Prediction Based on Song Lyrics

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December 10, 2014

Music Mood Prediction

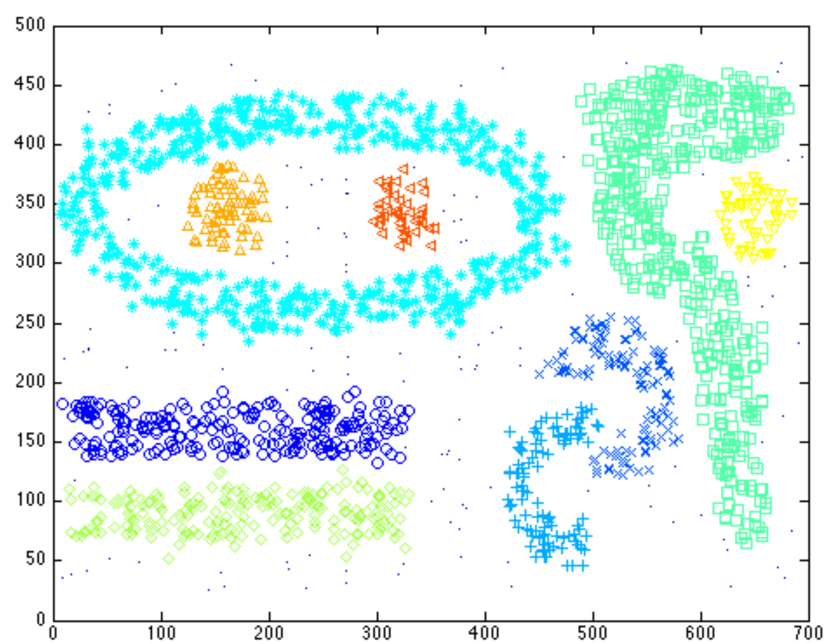
- We like to listen to music [1][2]
- Digital music libraries are growing
- Recommendation system for *happy* music (clinics, restaurants ...) & genre selection

[1] Thomas Schaefer, Peter Sedlmeier, Christine Sta¨dtler, and David Huron. The psychological functions of music listening. Frontiers in psychology, 4, 2013.

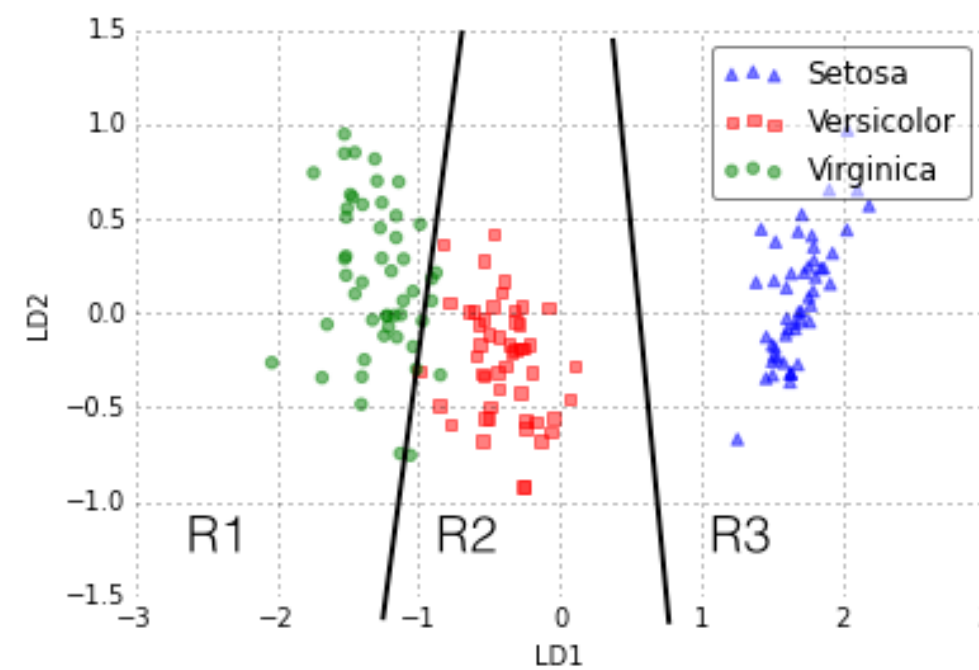
[2] Daniel Vaestfjaell. Emotion induction through music: A review of the musical mood induction procedure. Musicae Scientiae, 5(1 suppl):173–211, 2002.

Predictive Modeling

- Reinforcement learning
- Unsupervised learning
  - Hidden Markov models
  - Clustering
- **Supervised learning**
  - Ranking
  - **Classification**
  - Regression

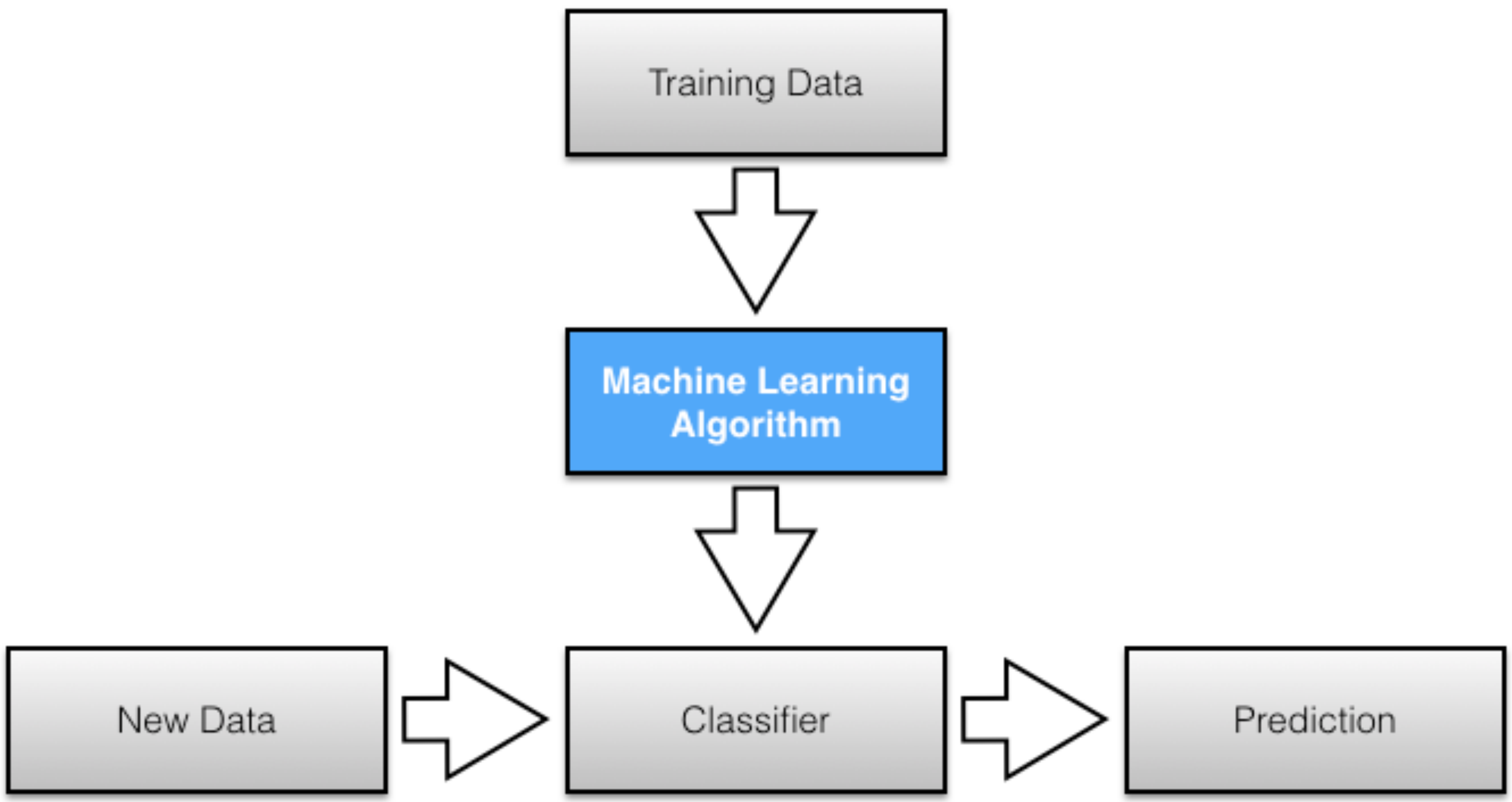


DBSCAN on a toy dataset

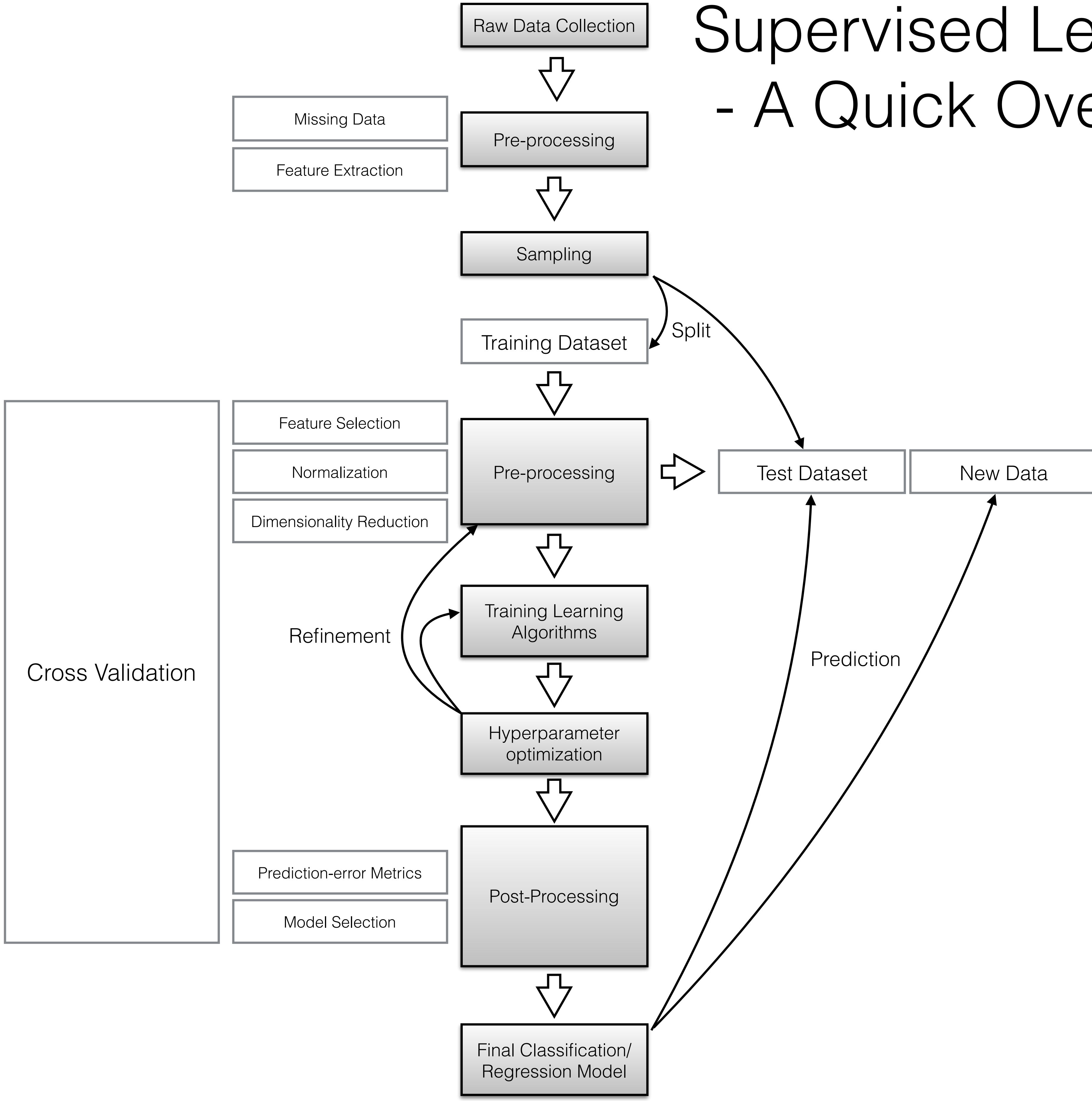


Naive Bayes on Iris (after LDA)

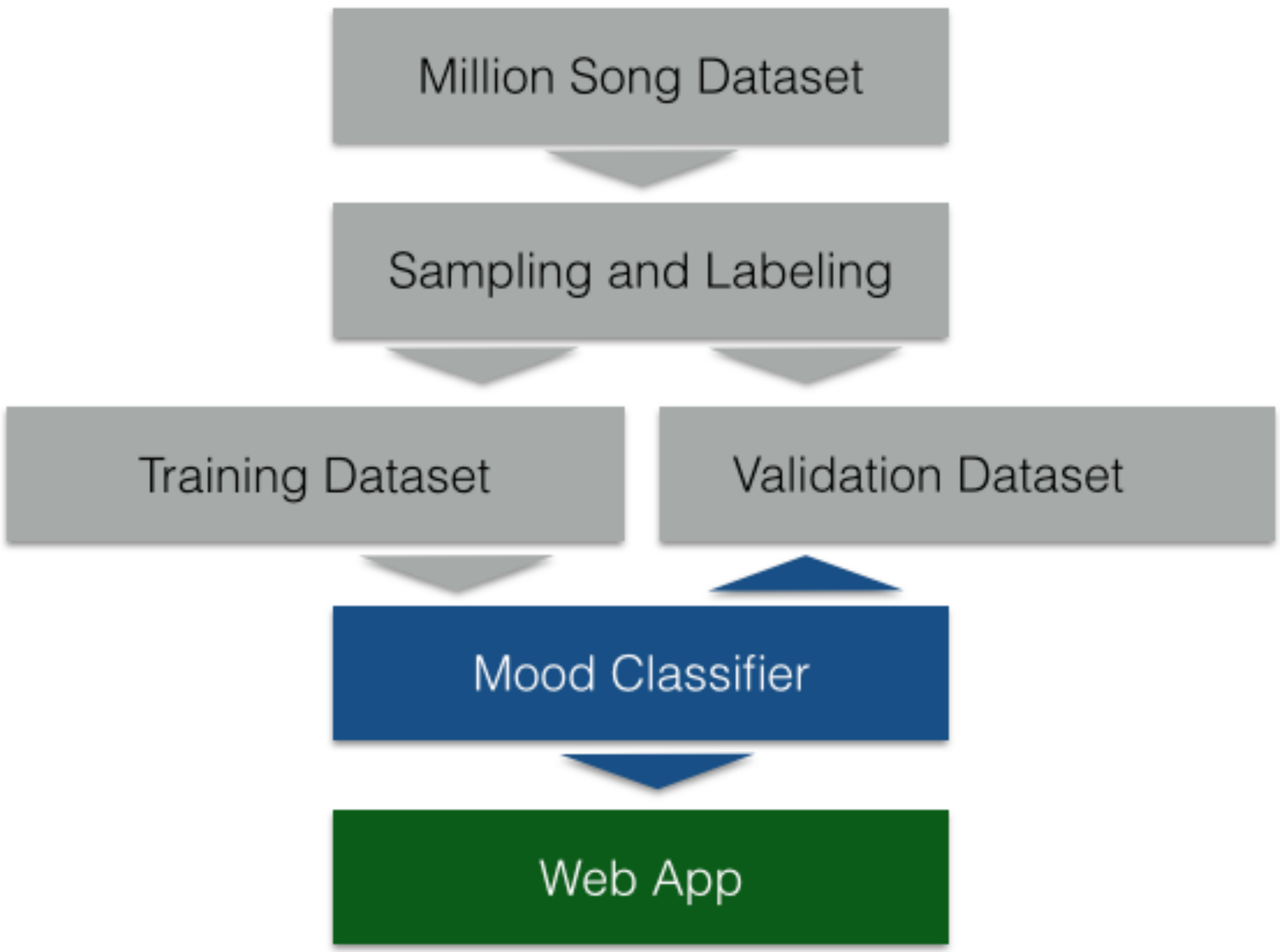
Supervised Learning In a Nutshell



Supervised Learning - A Quick Overview



MusicMood - The Plan



The Dataset

Million Song Dataset

Home | Getting the dataset | Code | Tutorial | Tasks / Demos | More data | Forum

Home » Getting the dataset

Getting the dataset

The logistics of distributing a 300 GB dataset are a little more complicated than for smaller collections. We do, however, provide a directly-downloadable subset for a quick look.

Before you start, you might want to review exactly what the dataset contains. Here is a page showing the contents of a single example file. You can download the corresponding raw HDF5 file here: TRAXLZU12903D05F94.h5.

http://labrosa.ee.columbia.edu/millionsong/

Sampling


1000 songs
for training
MILLION SONG DATASET
Lyrics available?
http://lyrics.wikia.com/Lyrics_Wiki
Lyrics in English?
Python NLTK
200 songs
for validation

Mood Labels

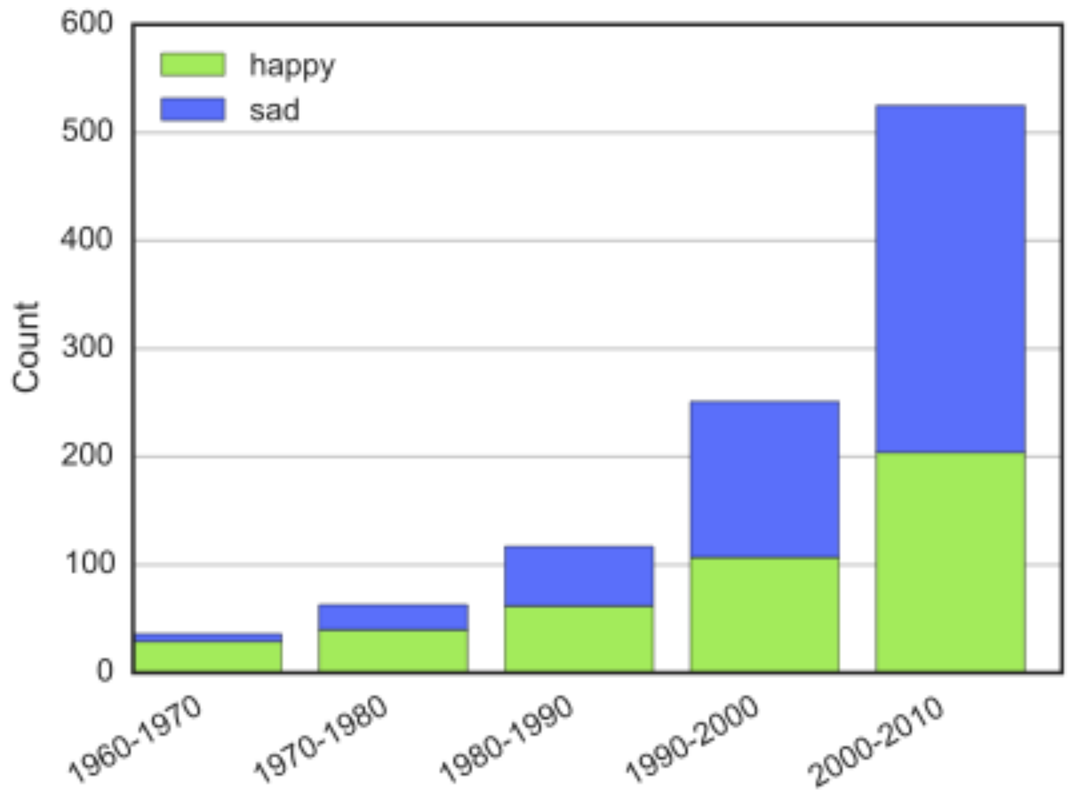
~~Downloading mood labels from Last.fm~~

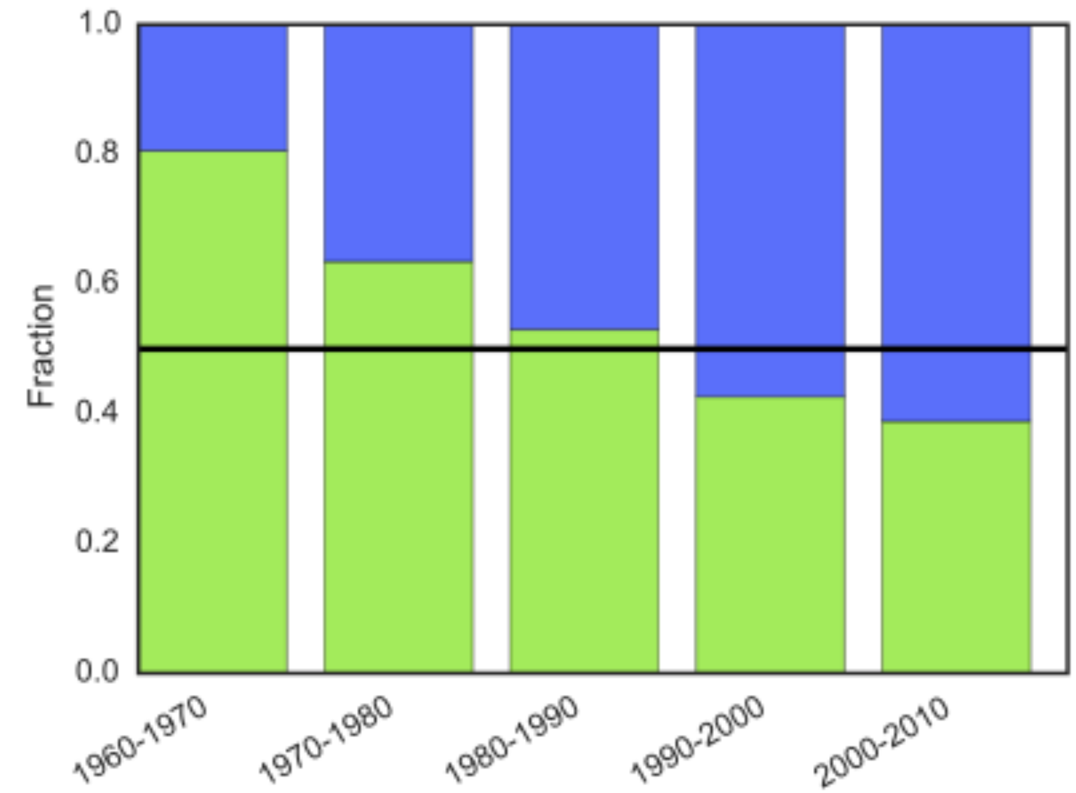
Manual labeling based on lyrics and listening

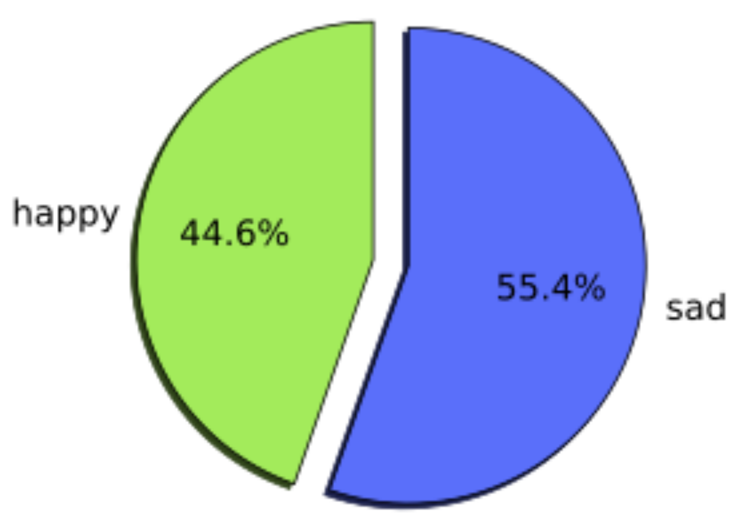
sad if ...

- Dark topic (killing, war, complaints about politics, ...)
- Artist in sorrow (lost love, ...)

Why so sad?
The mood of music over the last 50 years







[based on the 1000-song training dataset]

https://github.com/rasbt/musicmood

Sebastian Raschka 2014

Word Clouds

happy:

sad:

A Short Introduction to Naive Bayes Classification

Naive Bayes - Why?

- Small sample size, can outperform the more powerful alternatives [1]
- "Eager learner" (on-line learning vs. batch learning)
- Fast for classification and re-training
- Success in Spam Filtering [2]
- High accuracy for predicting positive and negative classes in a sentiment analysis of Twitter data [3]

[1] Pedro Domingos and Michael Pazzani. On the optimality of the simple bayesian classifier under zero-one loss. *Machine learning*, 29(2-3):103–130, 1997.

[2] Mehran Sahami, Susan Dumais, David Heckerman, and Eric Horvitz. A bayesian approach to filtering junk e-mail. In *Learning for Text Categorization: Papers from the 1998 workshop*, volume 62, pages 98–105, 1998.

[3] Alec Go, Richa Bhayani, and Lei Huang. Twitter sentiment classification using distant supervision. CS224N Project Report, Stanford, pages 1–12, 2009.

Bayes Classifiers
It's All About Posterior Probabilities

$$P\left(\omega_j \mid \mathbf{x}_i\right) = \frac{P\left(\mathbf{x}_i \mid \omega_j\right) \cdot P\left(\omega_j\right)}{P\left(\mathbf{x}_i\right)}$$

$$\text{posterior probability} = \frac{\text{conditional probability} \cdot \text{prior probability}}{\text{evidence}}$$

objective function: maximize the posterior probability

$$\text{predicted class label} \leftarrow \underset{j=1\ldots,m}{\arg\max}\; P\left(\omega_j \mid \mathbf{x}_i\right)$$

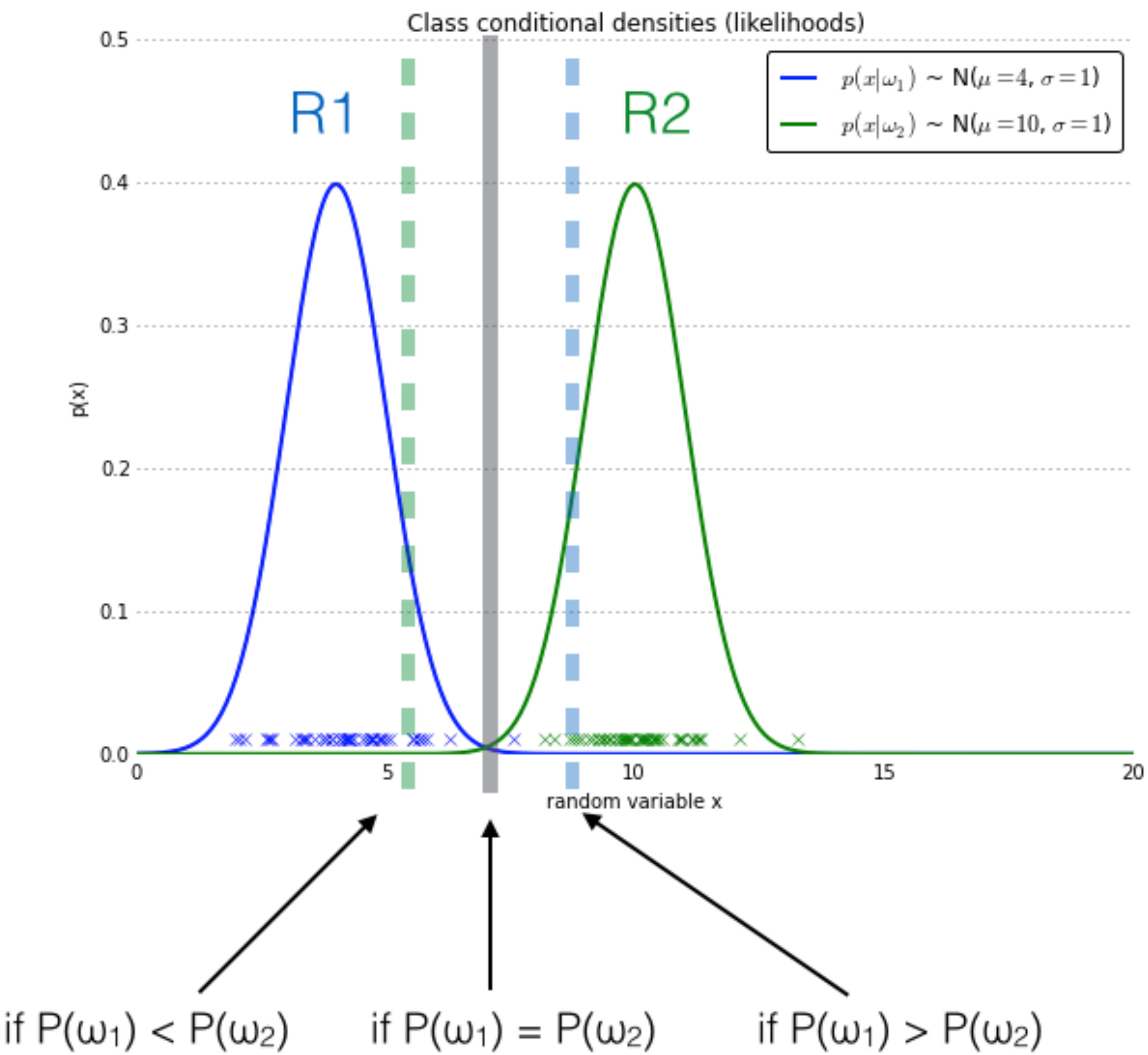
The Prior Probability

Maximum Likelihood Estimate (MLE)

$$\widehat{P}\left(\omega_j\right) = \frac{N_{\omega_j}}{N_c}$$

- N_{ω_j}: Count of samples from class ω_j.
- N_c: Count of all samples.

The Effect of Priors on the Decision Boundary



Class-Conditional Probability

Maximum Likelihood Estimate (MLE)

$$\widehat{P}\left(x_i \mid \omega_j\right) = \frac{N_{i,c}}{N_i} \qquad \left(i = \left(1, \ldots, d\right)\right)$$

- $N_{i,c}$: Count of feature x_i in class ω_j.
- $N_i c$: Count of feature x_i in all classes.

"chance of observing feature x_i given that it belongs to class ω_j "

Evidence

$$P(\mathbf{x}_i) = P\left(\mathbf{x}_i \mid \omega_j\right) \cdot P\left(\omega_j\right) + P\left(\mathbf{x}_i \mid \omega_j^C\right) \cdot P\left(\omega_j^C\right)$$

just a normalization factor,
can be omitted in decision rule:

$$\frac{P\left(\mathbf{x}_i \mid \omega_1\right) \cdot P(\omega_1)}{P(\mathbf{x}_i)} > \frac{P\left(\mathbf{x}_i \mid \omega_2\right) \cdot P(\omega_2)}{P(\mathbf{x}_i)}$$

$$\propto P\left(\mathbf{x}_i \mid \omega_1\right) \cdot P(\omega_1) > P\left(\mathbf{x}_i \mid \omega_2\right) \cdot P(\omega_2)$$

Naive Bayes Models

Gaussian Naive Bayes

$$P\left(x_{ik} \mid \omega\right) = \frac{1}{\sqrt{2\pi\sigma_\omega^2}} \exp\left(-\frac{\left(x_{ik} - \mu_\omega\right)^2}{2\sigma_\omega^2}\right),$$

$$P\left(\mathbf{x}_i \mid \omega\right) = \prod_{k=1}^{d} P\left(\mathbf{x}_{ik} \mid \omega\right)$$

for continuous variables

Naive Bayes Models

Multi-variate Bernoulli Naive Bayes

$$P\left(\mathbf{x}|\omega_j\right) = \prod_{i=1}^{m} P\left(x_i \mid \omega_j\right)^b \cdot \left(1 - P\left(x_i \mid \omega_j\right)\right)^{(1-b)} \quad (b \in 0, 1)$$

for binary features

Naive Bayes Models

Multinomial Naive Bayes

$$\widehat{P}\left(x_i \mid \omega_j\right) = \frac{\sum tf\left(x_i, d \in \omega_j\right) + \alpha}{\sum N_{d \in \omega j} + \alpha \cdot V}$$

$$P\left(\mathbf{x} \mid \omega_j\right) = P\left(x_1 \mid \omega_j\right) \cdot P\left(x_2 \mid \omega_j\right) \cdot \ldots \cdot P\left(x_n \mid \omega_j\right) = \prod_{i=1}^{m} P\left(x_i \mid \omega_j\right)$$

- x_i: A word from the feature vector $\mathbf{x}$ of a particular sample.
- $\sum tf\left(x_i, d \in \omega_j\right)$: The sum of raw term frequencies of word x_i from all documents in the training sample that belong to class ω_j.
- $\sum N_{d \in \omega j}$: The sum of all term frequencies in the training dataset for class ω_j.
- α: An additive smoothing parameter ($\alpha = 1$ for Laplace smoothing).
- V: The size of the vocabulary (number of different words in the training set).

Naive Bayes and Text Classification

Feature Vectors

The Bag of Words Model

- D_1: "Each state has its own laws."
- D_2: "Every country has its own culture."

	each	state	has	its	own	laws	every	country	culture
$\mathbf{x}_{D1}$	1	1	1	1	1	1	0	0	0
$\mathbf{x}_{D2}$	0	0	1	1	1	0	1	1	1
$\sum$	1	1	2	2	2	1	1	1	1

Tokenization and N-grams

"a swimmer likes swimming thus he swims"

- unigram (1-gram):

a	swimmer	likes	swimming	thus	he	swims

- bigram (2-gram):

a swimmer	swimmer likes	likes swimming	swimming thus	...

- trigram (3-gram):

a swimmer likes	swimmer likes swimming	likes swimming thus	...

Stemming and Lemmatization

Porter Stemming

A swimmer likes swimming, thus he swims.

↓

a	swimmer	like	swim	,	thu	he	swim	.

Lemmatization

A swimmer likes swimming, thus he swims.

↓

A	swimmer	like	swimming	,	thus	he	swim	.

Stop Word Removal

A swimmer likes swimming, thus he swims.

↓

swimmer	likes	swimming	,	swims	.

Term and Frequency

$$\text{normalized term frequency} = \frac{tf(t,d)}{n_d}$$

where

- $tf(t,d)$: Raw term frequency (the count of term t in document d).
- n_d: The total number of terms in document d.

Term Frequency - Inverse Document Frequency (Tf-idf)

$$\text{Tf-idf} = tf_n\left(t, d\right) \cdot idf\left(t\right)$$

Let $tf_n\left(d, f\right)$ be the normalized term frequency, and idf, the inverse document frequency, which can be calculated as follows

$$idf\left(t\right) = \log\left(\frac{n_d}{n_d\left(t\right)}\right),$$

where

- n_d: The total number of documents.
- $n_d\left(t\right)$: The number of documents that contain the term t.

Grid Search and 10-fold Cross Validation to Optimize F1

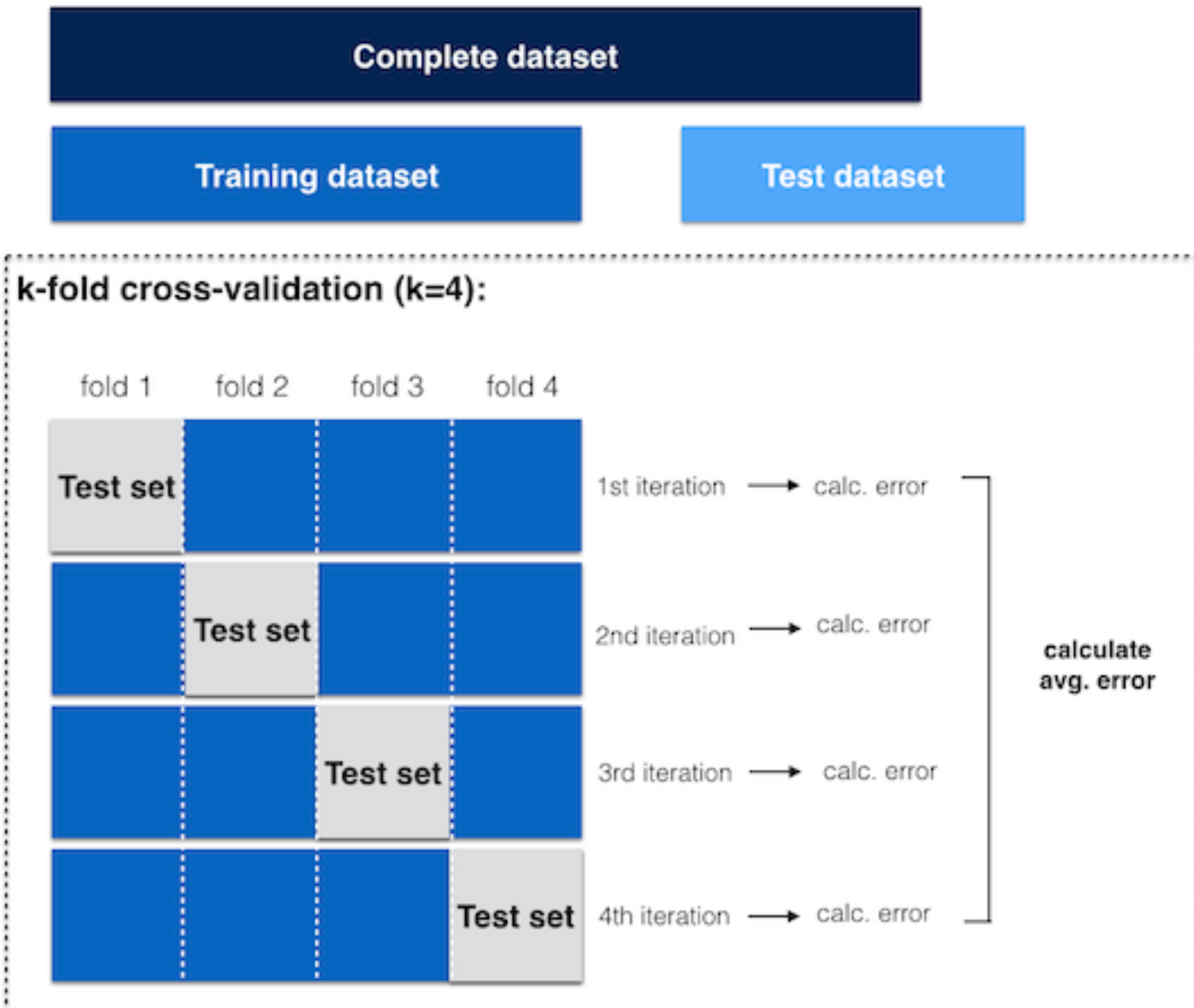
$$F1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

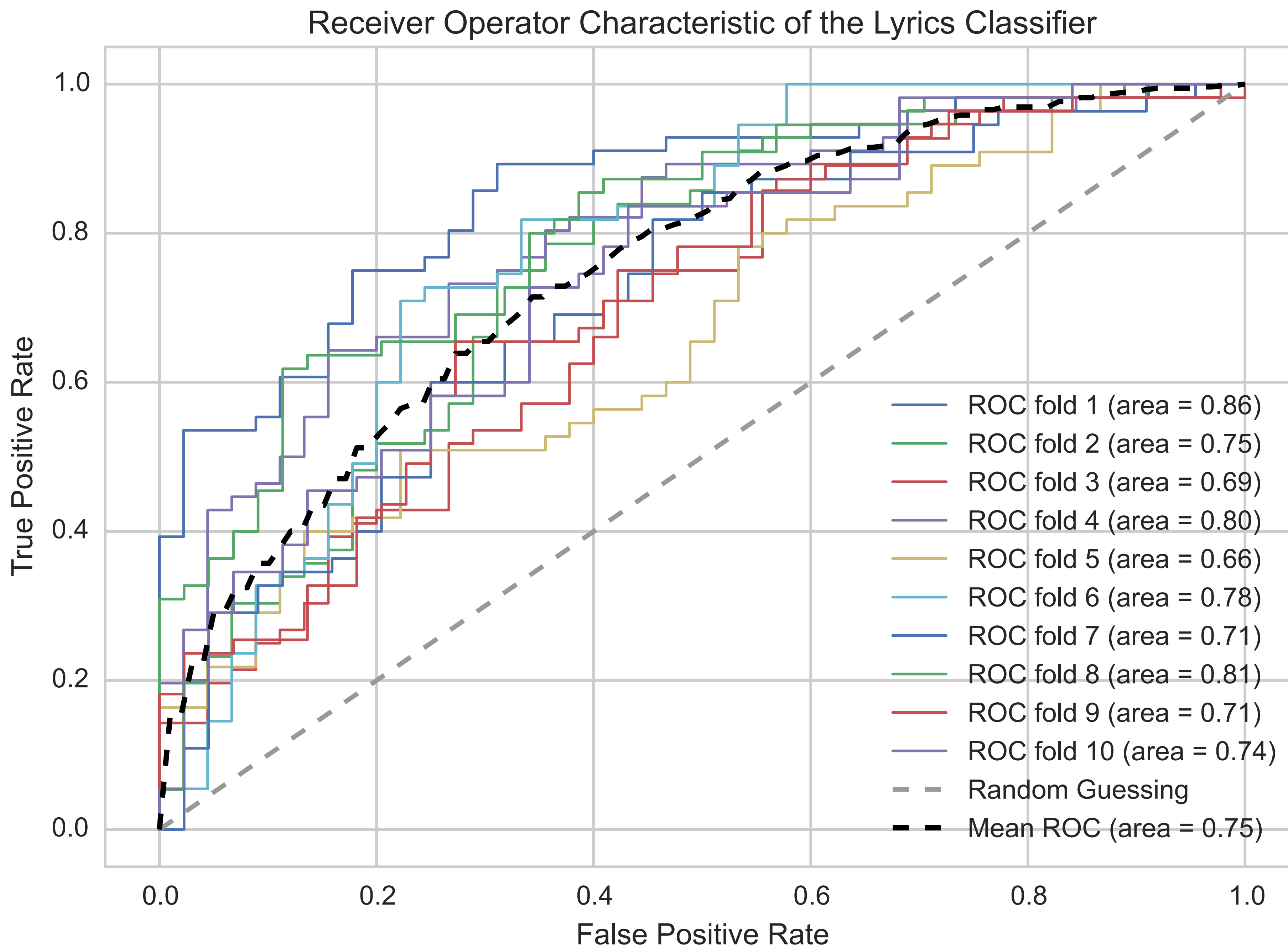
$$\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

- TP = true positive (happy predicted as happy)
- FP = false positive (sad predicted as happy)
- FN = false negative (happy predicted as sad)

K-Fold Cross Validation

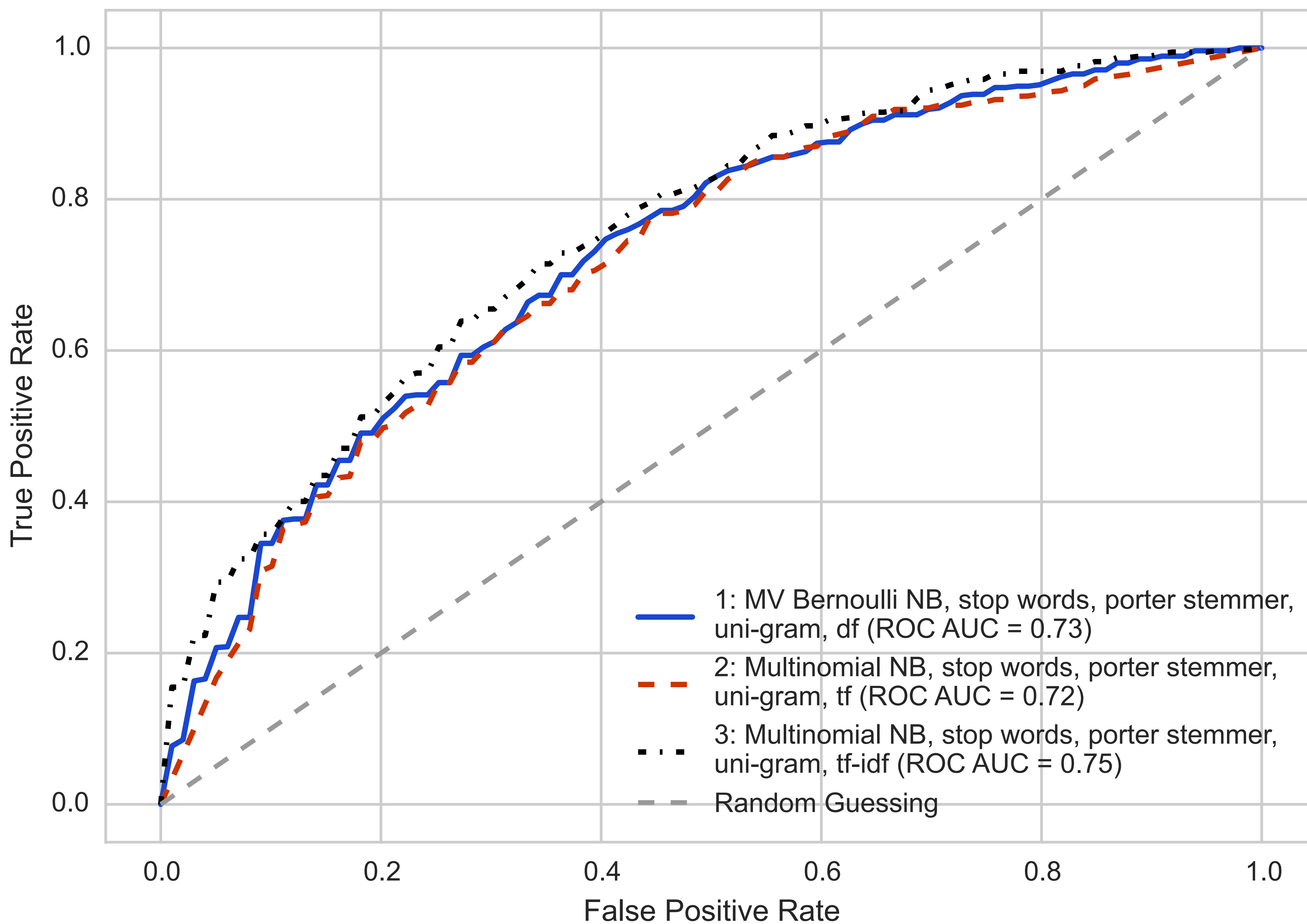


10-Fold Cross Validation After Grid Search



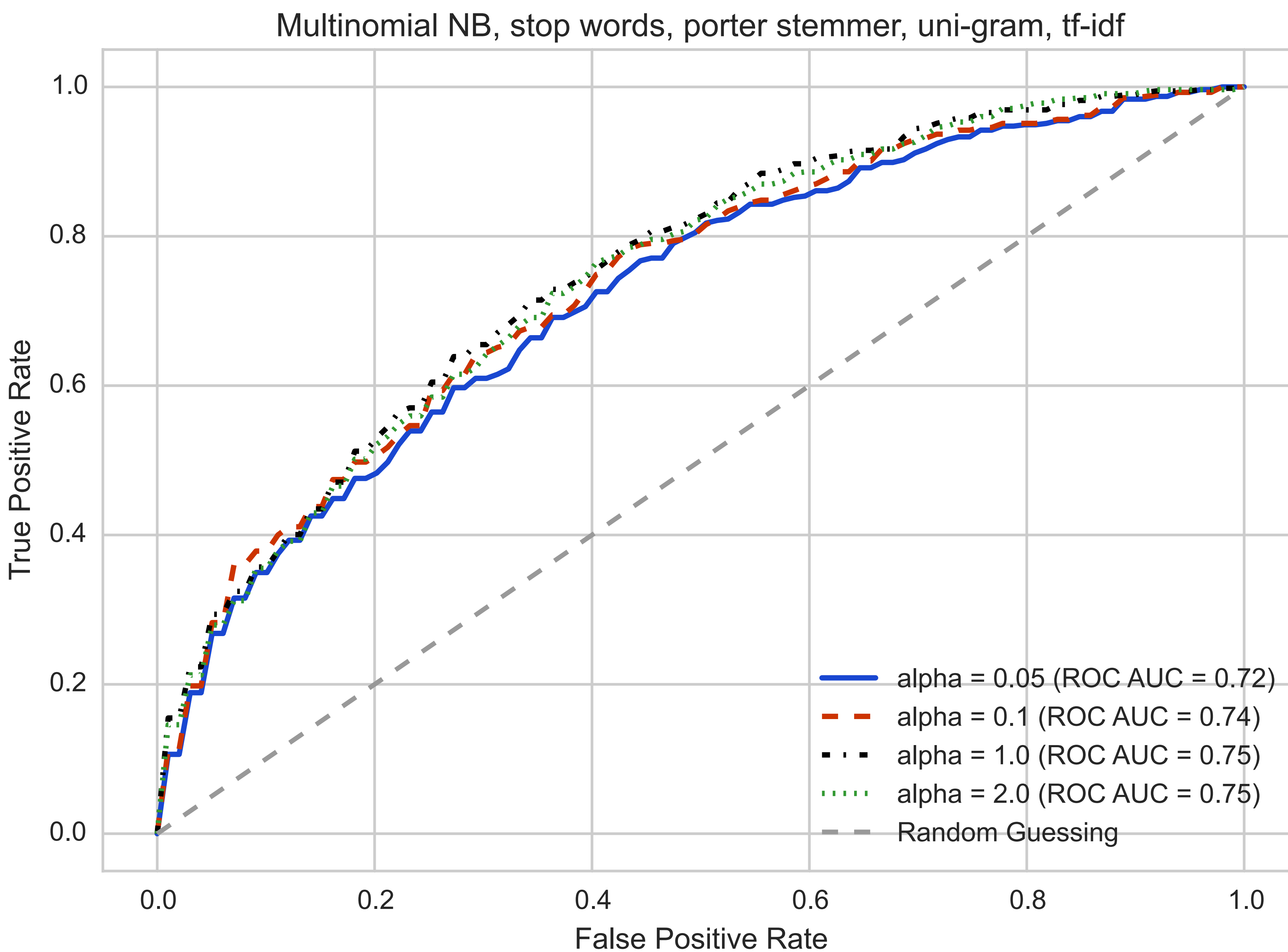
(final model)

10-fold Cross Validation (mean ROC)
Multinomial vs Multi-variate Bernoulli Naive Bayes

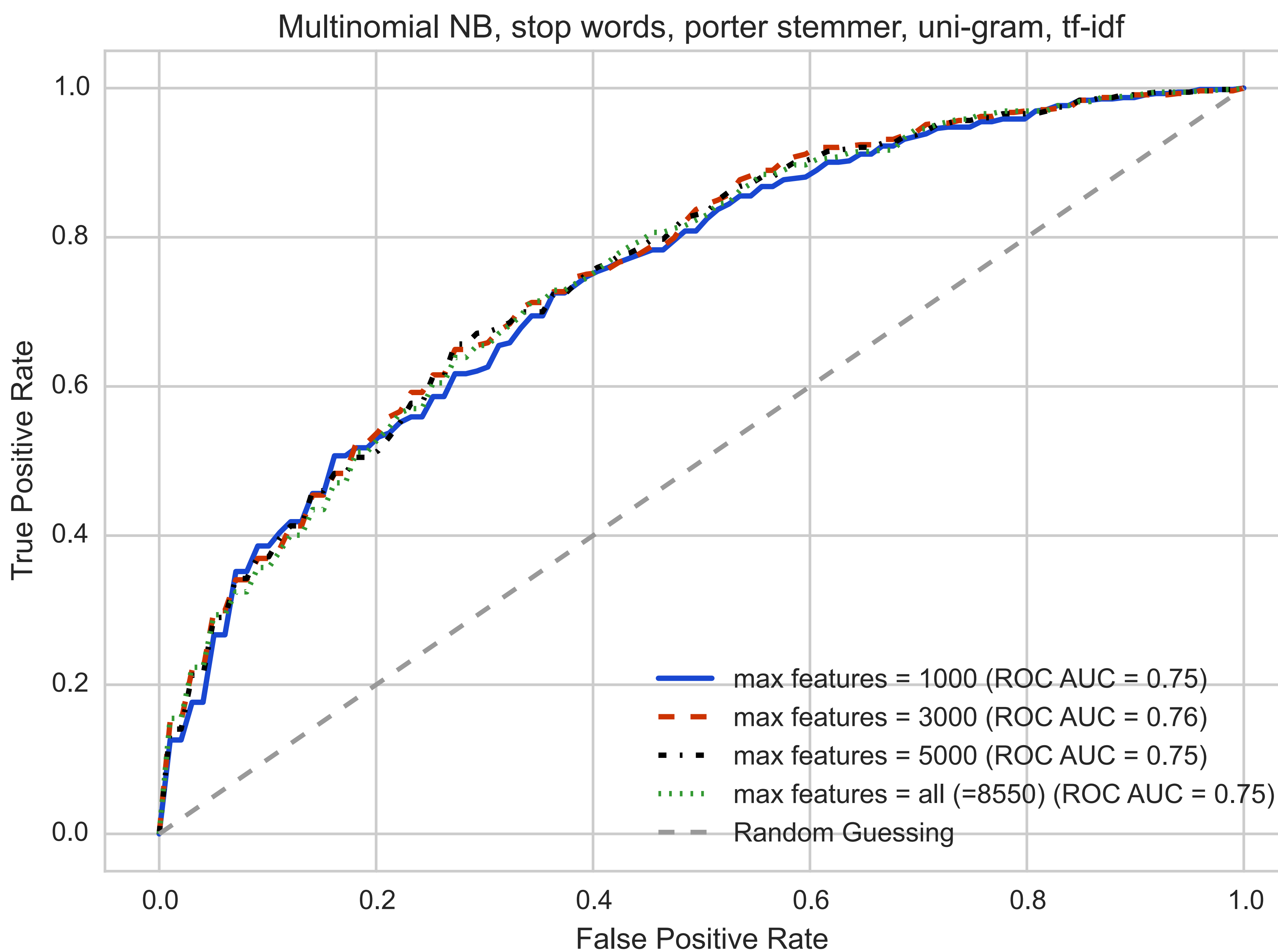


10-fold Cross Validation (mean ROC)

Multinomial Naive Bayes & Hyperparameter Alpha

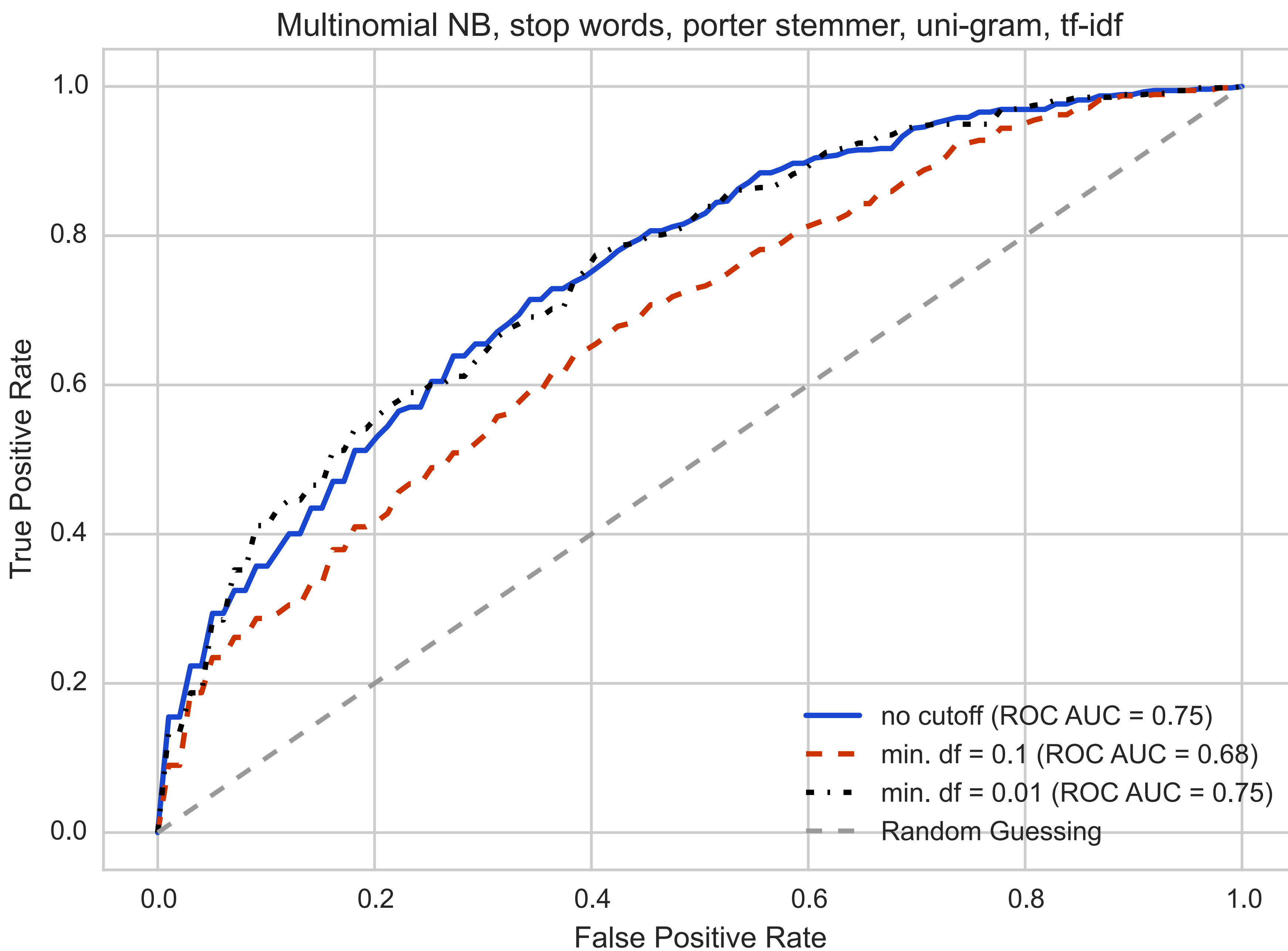


10-fold Cross Validation (mean ROC)
Multinomial Naive Bayes & Vocabulary Size



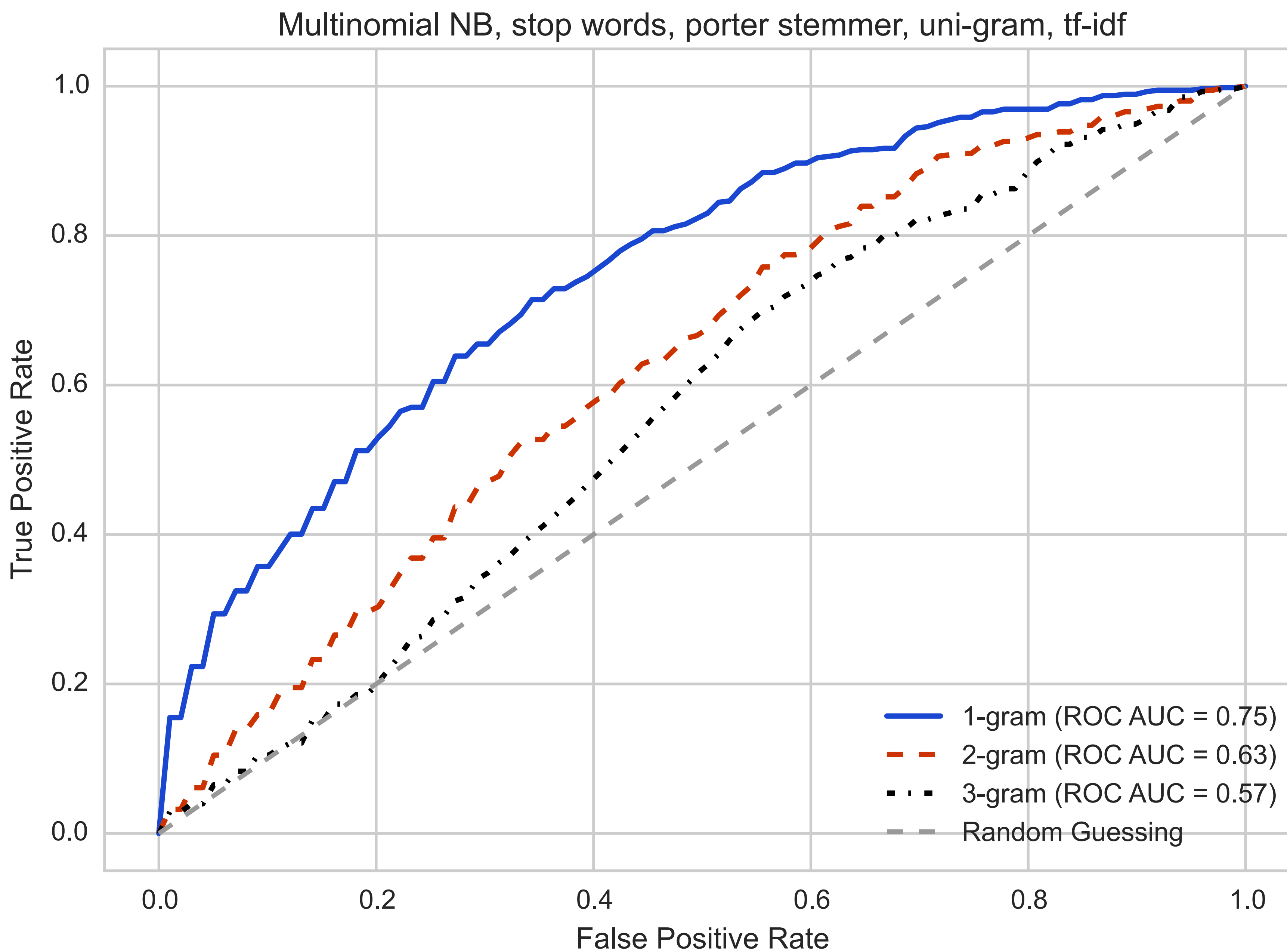
10-fold Cross Validation (mean ROC)

Multinomial Naive Bayes & Document Frequency Cut-off

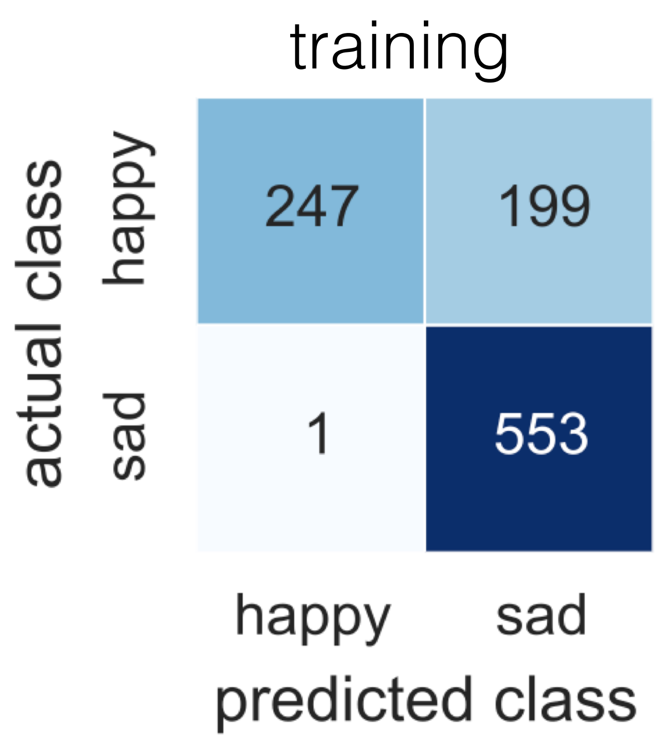


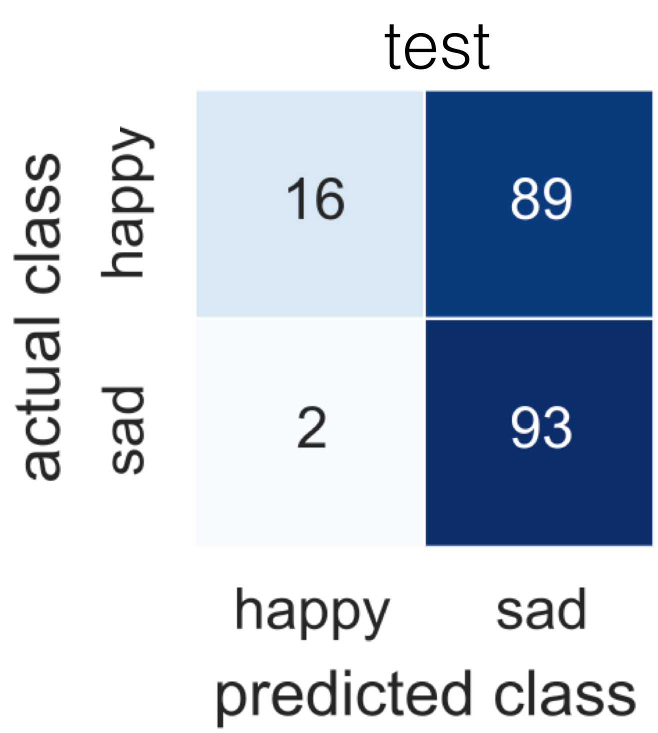
10-fold Cross Validation (mean ROC)

Multinomial Naive Bayes & N-gram Sequence Length



Contingency Tables of the Final Model





Performance metric	Training	Validation
Accuracy	80.00%	54.50%
Precision	99.60%	88.89%
Recall	55.38%	15.24%
F1-score	71.18%	26.02%
ROC auc	77.60%	56.57%

Live Demo

http://sebastianraschka.com/Webapps/musicmood.html

Artist name:

Song title:

Search Random song

Back to the overview

Flask

web development, one drop at a time

Artist name: Bob Dylan

Song title: Blowing in the wind

Lyrics:
How many roads must a man walk down Before you call him a man? Yes, 'n' how many seas must a white dove sail Before she sleeps in the sand? Yes, 'n' how many times must the cannon balls fly Before they're forever banned? The answer, my friend, is blowin' in the wind The answer is blowin' in the wind How many times must a man look up Before he can see the sky? Yes, 'n' how many ears must one man have Before he can hear people cry? Yes, 'n' how many deaths will it take till he knows That too many people have died? The answer, my friend, is blowin' in the wind The answer is blowin' in the wind How many years can a mountain exist Before it's washed to the sea? Yes, 'n' how many years can some people exist Before they're allowed to be free? Yes, 'n' how many times can a man turn his head Pretending he just doesn't see? The answer, my friend, is blowin' in the wind The answer is blowin' in the wind

Prediction: sad (probability 63.83%)

Try again

Listen to this song on YouTube.

I am looking forward to your feedback in order to improve the mood classifier! Clicking one of the two buttons below will add a new mood label to existing songs in the database, or a new database entry will be created if this song was not included in the training dataset, yet.

I think this song is happy sad

- 1332 lyrics
- 1350 mood labels

Future Plans

- Growing a list of mood labels (majority rule).

	artist	title	lyrics	mood
1256	lorde	team	[Intro] Wait 'til you'r…	happy
1257	kendrick lamar	swimming pools	[Bridge:] Pour up, dra…	sad
1258	radiohead	karma police	Karma police Arrest this m…	happy,sad
1259	pink floyd	see emily play	Pink Floyd Masters Of …	sad
1260	green day	holiday	(Say hey!) Hear the sou…	sad
1261	pharrell williams	happy	(from "Despicable …	happy,happy…
1262	john lennon	imagine	Imagine there's no Heaven It…	sad,sad
1263	taylor swift	blank space	Nice to meet you, where y…	happy
1264	alt-j	breezeblocks	She may contain t	
1265	metallica	one	I can't rememb	
1266	lynyrd skynyrd	free bird	(Allen Co Ronnie \	

- Performance comparisons of different machine learning algorithms.

- Genre prediction and selection based on sound.

Thank you!