

grapevine

a sommelier in your pocket

Motivation

Wine is an **expensive** hobby, and the majority of people have neither the time nor the money to discover their own **flavor palate**. Typically, the only claim one can make about a given glass of wine is whether or not it was enjoyable.

For this reason it is incredibly difficult for one to discover new wine. Our project looks to simplify the endeavor, through techniques in the realm of unsupervised learning and recommendation.

Formally, we define the problem as follows. Given design matrix X , we look to assign each example x to one of k clusters. Then we seek to output an optimal recommendation w .

written by

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Chambolle-Musigny Les Cras, 2008, \$65, Burgundy, ...

Candied cherry, cinnamon, violet and black currant notes ride the nervy acidity in this crisp red.

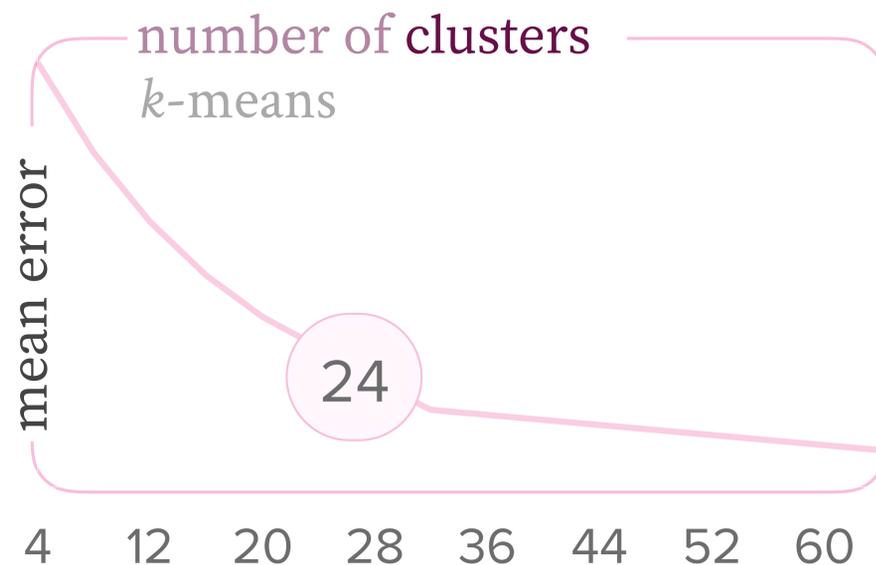
Preprocessing

0.172 0.163 0.274 0.126
Candied cherry, cinnamon, violet and
black currant notes ride the nervy
acidity in this crisp red. 0.449
0.465 0.143 0.413

Clustering

spice black cherry
currant blackberry licorice
red firm ripe plum

Recommendation



Pipeline

Our **dataset** consists of ~300k wine reviews, augmented by **name**, **price**, **rating**, **region**, **vintage**, and **county** (aggregated from WineSpectator.com).

We first **filter** out extremely common words, and then apply **tf-idf**; sommeliers are quite precise with their language, so a unique word across two distinct reviews could signal meaningful **similarity**.

We then **cluster** using mixture of **k-Gaussians** via **EM**, which reduces the search space drastically for **recommendation**. The optimal cluster count was found efficiently via k-means, using the **SSE** (Sum Squared Error) falloff as our success signal.

We finally **recommend** by sampling from a **Multinomial** over the k outcomes, weighted by **previous preferences**. Within the cluster, a previously preferred wine is sampled (with multivariate Gaussian noise) and becomes the **benchmark** for finding the two clusters with **highest probability**; within this space, we minimize the following **cost**:

$$J(\mathbf{w}, \mathbf{w}') = \frac{\text{price}(\mathbf{w}')}{\text{cost}(\mathbf{w}')} + \lambda \frac{\mathbf{w} \cdot \mathbf{w}'}{\|\mathbf{w}\| \cdot \|\mathbf{w}'\|}$$

Future Work

Tuning **score**, **price** and **similarity** hyper-parameters within cost; implementing **GloVE vectors** over **tf-idf** scores.