|   | ! pip install hdbscan       ! python -m spacy download en_core_web_sm  |
|---|--|
|   | Book Crossing - Classification (Unsupervised)  |
| In [3]:   | <pre>%matplotlib inline import scipy import seaborn as sns import matplotlib.pyplot as plt import pandas as pd import numpy as np</pre>  |
|   | <pre>sns.set() palette = sns.color_palette("icefire") plt.style.use('ggplot') sns.set_context("talk")</pre>  |
| In [127]:<br>In [128]:  | <pre>dataset = pd.read_csv('book_crossing.classification.cleaned.csv')  dataset['age'] = dataset['age'].astype(np.float64) dataset['book_rating'] = dataset['book_rating'].astype('category') dataset['book_title'] = dataset['book_title'].astype('category') dataset['book_author'] = dataset['book_author'].astype('category')</pre>  |
| In [136]:<br>Out[136]:  | <pre>dataset['year_of_publication'] = dataset['year_of_publication'].astype(np.float64) dataset['publisher'] = dataset['publisher'].astype('category') dataset['country'] = dataset['country'].astype('category')</pre>  |
| In [139]:<br>Out[139]:  | dataset['book_author'].cat.categories.shape  |
| Out[140]:   | (11311,)  dataset['country'].cat.categories.shape  |
| <pre>In [6]: Out[6]:</pre>                                    | dataset.head()       age     book_rating     book_title     book_author     year_of_publication     publisher     country       0     34.0     mid     Clara Callan     Richard Bruce Wright     2001.0     HarperFlamingo Canada     canada       1     30.0     high     Clara Callan     Richard Bruce Wright     2001.0     HarperFlamingo Canada     canada   |
| In [7]:   | 2 34.0 high Clara Callan Richard Bruce Wright 2001.0 HarperFlamingo Canada canada 3 34.0 high Clara Callan Richard Bruce Wright 2001.0 HarperFlamingo Canada canada 4 34.0 high Clara Callan Richard Bruce Wright 2001.0 HarperFlamingo Canada canada  dataset.info()  |
|   | <pre><class 'pandas.core.frame.dataframe'=""> RangeIndex: 364570 entries, 0 to 364569 Data columns (total 7 columns): # Column</class></pre>   |
|   | 2 book_ittle 364570 non-null category 3 book_author 364570 non-null category 4 year_of_publication 364570 non-null float64 5 publisher 364570 non-null category 6 country 364570 non-null category dtypes: category(5), float64(2) memory usage: 19.1 MB   |
| In [8]:   | <pre>c_dataset = dataset["book_title"].astype(str) + " " + \</pre>   |
| In [9]:   | for ex in c_dataset.sample(frac=0.2)[:5]:     print(ex)  The Vanishing Vampire (The Accidental Monsters , No 1) David Lubar Scholastic 1997.0 12.0 usa  REMEMBER ME Mary Higgins Clark Simon & Schuster 1994.0 34.0 usa  The Mummy or Ramses the Damned Anne Rice Ballantine Books 1991.0 22.0 usa   |
|   | Bittersweet Rain Sandra Brown Warner Books 2000.0 34.0 usa Arthur Stephen R. Lawhead Zondervan Publishing Company 1996.0 21.0 usa  small_dataset = dataset.copy().sample(frac=0.03)  small_dataset.shape   |
|   | <pre>(10937, 7)  c_dataset_small = small_dataset["book_title"].astype(str) + " " + \</pre>   |
| In [95]:  | small_dataset["country"].astype(str)   |
| In [96]:  |  |
| In [97]:  | <pre>from sklearn.cluster import KMeans, DBSCAN, Birch, MiniBatchKMeans, SpectralClustering, AgglomerativeClustering, MeanShift, Affi nityPropagation, OPTICS from sklearn.decomposition import TruncatedSVD set_config(display='diagram')</pre>   |
|   | <pre>definit(self, nlp):     self.nlp = nlp     self.dim = 300  def fit(self, X, y):     return self</pre>   |
| In [98]:  | <pre>def transform(self, X):     # Doc.vector defaults to an average of the token vectors.     # https://spacy.io/api/doc#vector     return [self.nlp(text).vector for text in X]  X, y = c_dataset, dataset['book_rating']</pre>  |
| -   | <pre>X_small, y_small = c_dataset_small, small_dataset['book_rating']  target_names = ['low', 'mid', 'high']  Unsupervised Models</pre>  |
|   | <ul> <li>KMedoids</li> <li>AgglomerativeClustering</li> <li>DBSCAN</li> <li>KMeansClustering</li> <li>HDBSCAN</li> </ul>   |
| In [102]:   | <pre>• MiniBatchKMeans  """  km = KMeans(n_clusters=3) # works (needs remap of output)  dbscan = DBSCAN() birch = Birch() # crash</pre>  |
| 2500  | <pre>mbkm = MiniBatchKMeans() # works (needs remap of output) sc = SpectralClustering() # crash ac = AgglomerativeClustering() # sparse not supported ms = MeanShift(bandwidth=3) # sparse not supported ap = AffinityPropagation() # crash oo = OPTICS() # sparse not supported """</pre>   |
|   | '\nkm = KMeans(n_clusters=3) # works (needs remap of output)\ndbscan = DBSCAN()\nbirch = Birch() # crash\nmbkm = MiniBatchKMean s() # works (needs remap of output)\nsc = SpectralClustering() # crash\nac = AgglomerativeClustering() # sparse not supported\n ms = MeanShift(bandwidth=3) # sparse not supported\nap = AffinityPropagation() # crash\noo = OPTICS() # sparse not supported\n'  from time import time  def fit_model(algorithm, data):  |
|   | <pre>t1 = time() X, y = data print(f'\nStarted Training {algorithmclassname} on X: {X.shape} y: {y.shape}')</pre>  |
|   | <pre>embeddings_pipeline = Pipeline(     steps=[</pre>   |
|   | <pre># train the model embeddings_pipeline.fit(X, y)  print(f"\nEvaluating model on X_test: {X.shape} y_test: {y.shape}")  # test the model y true = y.copy()</pre>  |
|   | <pre>y_true = y.copy()  if isinstance(embeddings_pipeline['clusterer'], (AgglomerativeClustering, DBSCAN, OPTICS, HDBSCAN)):     y_pred = embeddings_pipeline['clusterer'].labels_ else:     y_pred = embeddings_pipeline.predict(X)  y_pred = np.array(list(map(lambda x: "low" if x == 0 else "mid" if x == 1 else "high", y_pred)))</pre>   |
|   | <pre>y_pred = np.array(list(map(lambda x: "low" if x == 0 else "mid" if x == 1 else "high", y_pred)))  # get the classification report print(f"\nClassification Report for {algorithmclassname}}") print(classification_report(y_true, y_pred, target_names=target_names, labels=target_names))  acc_score = accuracy_score(y_true, y_pred) bal_score = balanced_accuracy_score(y_true, y_pred)</pre>  |
|   | <pre>bal_score = balanced_accuracy_score(y_true, y_pred)  print(f"\nAccuracy Score: {acc_score}")  print(f"Balanced Accuracy Score: {bal_score}")  print()  # show the confusion matrix  cmmat_table = pd.DataFrame({'y_true': y_true, 'y_pred': y_pred})</pre>  |
|   | <pre>conmat = pd.crosstab(cmmat_table.y_true, cmmat_table.y_pred, rownames=['Actual'], colnames=['Predicted'], margins=True, norm alize='all') ax = plt.axes() sns.set(rc={'figure.figsize':(9, 7)}) sns.heatmap(conmat, annot=True, ax=ax) ax.set_title(f'{algorithmclassname}}') plt.show()</pre>  |
|   | <pre>plt.show() print()  t2 = time()  print(f'Trained {algorithmclassname} in {(t2 - t1)}s')  return embeddings_pipeline</pre>   |
| In [107]:   | KMedoids Clustering  from sklearn_extra.cluster import KMedoids  |
|   | <pre>kmedoids = KMedoids(n_clusters=3, max_iter=1)  clf = fit_model(algorithm=kmedoids, data=(X_small, y_small))  Started Training KMedoids on X: (10937,) y: (10937,)  Evaluating model on X_test: (10937,) y_test: (10937,)</pre>  |
|   | Classification Report for KMedoids   |
|   | accuracy 0.31 10937 macro avg 0.33 0.32 0.26 10937 weighted avg 0.50 0.31 0.37 10937  Accuracy Score: 0.30785407332906645 Balanced Accuracy Score: 0.3184037656596693  |
|   | KMedoids  0.18 0.22 0.19 0.58  |
|   | 0.0063 0.0072 0.0076 0.021 −0.6 −0.8   |
|   | O.12 O.16 O.12 O.4 -0.2  |
|   | ■ 0.3 0.38 0.32 1  high low mid All Predicted  |
| In [110]:<br>Out[110]:  | Trained KMedoids in 223.7921495437622s  clf  Pipeline  SpacyVectorTransformer  |
|   | TruncatedSVD KMedoids  |
| In [111]:<br>In [112]:  | Agglomerative Clustering  aggc = AgglomerativeClustering(n_clusters=3)  clf = fit_model(algorithm=aggc, data=(X_small, y_small))   |
|   | Started Training AgglomerativeClustering on X: (10937,) y: (10937,)  Evaluating model on X_test: (10937,) y_test: (10937,)  Classification Report for AgglomerativeClustering precision recall f1-score support  |
|   | low 0.02 0.37 0.04 231 mid 0.37 0.31 0.34 4333 high 0.57 0.24 0.34 6373  accuracy 0.27 10937 macro avg 0.32 0.31 0.24 10937 weighted avg 0.48 0.27 0.33 10937  |
|   | Accuracy Score: 0.2729267623662796 Balanced Accuracy Score: 0.30877414843520845  AgglomerativeClustering  -1.0   |
|   | 년<br>- 0.14 0.24 0.2 0.58<br>- 0.8   |
|   | No.0058 0.0079 0.0075 0.021 -0.6    Post   |
|   | - 0.2<br>■ 0.25 0.42 0.33 1  |
| In [113]:<br>Out[113]:  |  |
| Out[113]:   | Pipeline  SpacyVectorTransformer  TruncatedSVD  AgglomerativeClustering  |
| In [114]:   |  |
| In [115]:   | Started Training DBSCAN on X: (10937,) y: (10937,)  Evaluating model on X_test: (10937,) y_test: (10937,)  Classification Report for DBSCAN  |
|   | precision recall f1-score support  low 0.00 0.00 0.00 231 mid 0.20 0.00 0.00 4333 high 0.58 1.00 0.74 6373  accuracy 0.58 10937 macro avg 0.26 0.33 0.25 10937   |
|   | macro avg 0.26 0.33 0.25 10937<br>weighted avg 0.42 0.58 0.43 10937<br>Accuracy Score: 0.5818780287098839<br>Balanced Accuracy Score: 0.3328872224199264   |
|   | DBSCAN  -1.0  -0.8   |
|   | O.021  |
|   | 1     0.4     0.00027     9.1e-05     0.4       2     1     0.00091     0.00046     1  |
| -   | high low mid All Predicted  Trained DBSCAN in 116.67007970809937s  |
| In [116]:<br>Out[116]:  | Pipeline SpacyVectorTransformer TruncatedSVD   |
| 23.000  | Means Clustering   |
| In [117]:<br>In [118]:  | <pre>kmeans = KMeans(n_clusters=3, n_init=3)  clf = fit_model(algorithm=kmeans, data=(X_small, y_small))  Started Training KMeans on X: (10937,) y: (10937,)  Evaluating model on X_test: (10937,) y_test: (10937,)</pre>  |
|   | Classification Report for KMeans   |
|   | accuracy 0.32 10937<br>macro avg 0.34 0.34 0.27 10937  |
|   | weighted avg 0.50 0.32 0.38 10937  Accuracy Score: 0.31535155892840816  Balanced Accuracy Score: 0.33658550914710594   |
|   | Accuracy Score: 0.31535155892840816 Balanced Accuracy Score: 0.33658550914710594  KMeans  -1.0   |
|   | Accuracy Score: 0.31535155892840816 Balanced Accuracy Score: 0.33658550914710594  KMeans  -1.0  -0.8  0.0062 0.0084 0.0065 0.021  -0.6   |
|   | Accuracy Score: 0.31535155892840816 Balanced Accuracy Score: 0.33658550914710594  KMeans  -1.0  -0.8   |
|   | Accuracy Score: 0.31535155892840816 Balanced Accuracy Score: 0.33658559914710594    Main   |
| In [119]:<br>Out[119]:  | Accuracy Score: 0.31535155892840816 Balanced Accuracy Score: 0.33658559914710594  KMeans  0.2 0.23 0.16 0.58  0.0062 0.0084 0.0065 0.021  0.13 0.16 0.1 0.4  0.34 0.4 0.27 1  high low Predicted mid All  Predicted Means in 222.765841960906985   |
|   | Accuracy Score: 0.31535155892840816 Balanced Accuracy Score: 0.33658559914710594    NAMeans  |
| Out[119]: In [120]: In [121]:                                 | Accuracy Score: 0.31535155892848816 Balanced Accuracy Score: 0.33585892848816  83  |
| Out[119]: In [120]: In [121]:                                 | Accuracy Score: 0.3153515892840816 Balanced Accuracy Score: 0.33658559914710594    Means   |
| Out[119]: In [120]: In [121]:                                 | Accuracy Score: 0.3153515802Ad0816 Relatinced Accuracy Score: 0.3365559014718594  RMeans  O2 023 010 050  RMeans  O34 04 027 1  Injuh low Predicted  Pipeline  SpacyVectorTransformee  Truncate5VD  Welsans  HDBSCAN  From hdbscan import b085CMI  hacan = MDSCAMI(min_cluster_size-3)  cif = fit_model(algorithm-iscan, data-(X_small, y_small))  Started Fraining #MDSCAMI (min_cluster_size-3)  cif = fit_model(algorithm-iscan, data-(X_small, y_small))  Started Fraining #MDSCAMI (min_cluster_size-3)  cif = fit_model(algorithm-iscan, data-(X_small, y_small))  Started Fraining #MDSCAMI on X_test: (18937,) y, (18937,)  Evaluating model on X_test: (18937,) y, test: (18937,)  Lassification Report for MDSCAMI precision recall fi-score support  Inw 0.00 0.00 0.00 0.00 0.00 0.33 0.25 10937  accuracy 0.30 0.33 0.25 10937  |
| Out[119]: In [120]: In [121]:                                 | Accuracy Score: 0.335335502808316 Balanced Accuracy Score: 0.33658539014718594  Realised Accuracy Score: 0.38658539014718594  Realised Accuracy Score: 0.3865858918718694399   |
| Out[119]: In [120]: In [121]:                                 | Accuracy Score: 0.335355500386016 Balanced Accuracy Score: 0.3358550014710594  IMmars  |
| Out[119]: In [120]: In [121]:                                 | Accuracy Score: 0.318515380244016 Balanced Accuracy Score: 0.3268698914708944  |
| Out[119]: In [120]: In [121]:                                 | Accuracy Score: 0.3363558044738944  ### COST   |
| Out[119]: In [120]: In [121]:                                 | Accuracy Score: 0.315315560244616 Balanced Accuracy Score: 0.3253636984738994    Common  |
| Out[119]: In [120]: In [121]:                                 | ### Accuracy Score: 8.135515500048500 ###################################  |
| Out[119]:  In [120]:  In [121]:  In [122]:                    | December   0.0000   Dece   |
| <pre>Out[119]: In [121]: In [122]:  In [123]: Out[123]:</pre> | ### ACCOUNTS   \$18555550244816   \$100  |
| <pre>Out[119]: In [120]: In [121]: In [122]: Out[123]:</pre>  | ### PROJECT   ### PROJETT   ### PROJECT   ### PROJECT   ### PROJECT   ### PROJECT   ## |
| Out[119]: In [121]: In [122]: In [123]: Out[123]:             | ### Page 1   |
| <pre>Out[119]: In [120]: In [121]: In [122]: Out[123]:</pre>  | ### Part   |
| Out[119]: In [121]: In [122]: In [123]: Out[123]:             | ### Company Commerce -0.1935/1956/1956/1956/1956/1956/1956/1956/195  |
| Out[119]: In [121]: In [122]: In [123]: Out[123]:             | March   Marc   |
| Out[119]: In [121]: In [122]: In [123]: Out[123]:             | ### ### ##############################   |
| Out[119]: In [121]: In [122]: In [123]: Out[123]:             | ### Common Common & Michael Common Co |