**By:Brian Kim** In [1]: import numpy as np import pandas as pd from plotnine import \* from sklearn.cluster import KMeans import warnings warnings.filterwarnings('ignore') web = pd.read csv("Subscriber Information (Clean) Version 5.csv") In [2]: K-Means Clustering Web In [3]: ggplot(web, aes(x = 'PCA X', y = 'PCA Y')) + geom point()0.5 --0.5 --0.50.5 PCA X Out[3]: <ggplot: (104809092749)> In [4]: web.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 25291 entries, 0 to 25290 Data columns (total 71 columns): Purchase Amounts 25291 non-null float64 Duration 25291 non-null int64 Send\_Count 25291 non-null int64 Open\_Count 25291 non-null int64 Click Count 25291 non-null int64 Unique\_Open\_Count 25291 non-null int64 Unique\_Click\_Count 25291 non-null int64 Start 25291 non-null int64 Other 25291 non-null int64 Completed 25291 non-null int64 25291 non-null int64 NULL Onboarding 25291 non-null int64 25291 non-null int64 App\_Launch\_Times Total\_Time\_Launched 25291 non-null int64 Language\_ALL 25291 non-null float64 Language ENG 25291 non-null float64 25291 non-null float64 Language ESP Language\_FRA 25291 non-null float64 Language\_ITA 25291 non-null float64 25291 non-null float64 Language\_Other Subscription\_Type\_Lifetime 25291 non-null float64 Subscription\_Type\_Limited 25291 non-null float64 25291 non-null float64 Subscription\_Event\_Type\_INITIAL\_PURCHASE Subscription\_Event\_Type\_RENEWAL 25291 non-null float64 Purchase Store App 25291 non-null float64 Purchase\_Store\_Web 25291 non-null float64 Demo User No 25291 non-null float64 25291 non-null float64 Demo\_User\_Yes Free\_Trial\_User\_No 25291 non-null float64 Free\_Trial\_User\_Yes 25291 non-null float64 25291 non-null float64 Auto\_Renew\_Off Auto\_Renew\_On 25291 non-null float64 Country Europe 25291 non-null float64 25291 non-null float64 Country\_Other Country\_US/Canada 25291 non-null float64 User\_Type\_Consumer 25291 non-null float64 User\_Type\_Other 25291 non-null float64 25291 non-null float64 Lead\_Platform\_App 25291 non-null float64 Lead\_Platform\_Unknown Lead\_Platform\_Web 25291 non-null float64 Email Subscriber No 25291 non-null float64 Email\_Subscriber\_Yes 25291 non-null float64 25291 non-null float64 Push\_Notifications\_No 25291 non-null float64 Push\_Notifications\_Yes PCA X 25291 non-null float64 PCA Y 25291 non-null float64 PCA1 25291 non-null float64 PCA2 25291 non-null float64 PCA3 25291 non-null float64 25291 non-null float64 PCA4 PCA5 25291 non-null float64 25291 non-null float64 PCA6 PCA7 25291 non-null float64 25291 non-null float64 PCA8 25291 non-null float64 PCA9 PCA10 25291 non-null float64 PCA11 25291 non-null float64 PCA12 25291 non-null float64 25291 non-null float64 PCA13 25291 non-null object Language Subscription Type 25291 non-null object Subscription Event Type 25291 non-null object 25291 non-null object Purchase\_Store Demo User 25291 non-null object Free Trial User 25291 non-null object Auto Renew 25291 non-null object 25291 non-null object Country User\_Type 25291 non-null object Lead Platform 25291 non-null object Email\_Subscriber 25291 non-null object 25291 non-null object Push\_Notifications dtypes: float64(46), int64(13), object(12) memory usage: 13.7+ MB K-Means off all Variables In [5]: x = web.iloc[:, 0:44]Х Out[5]: Purchase\_Amounts Duration Send\_Count Open\_Count Click\_Count Unique\_Open\_Count Unique\_Click\_Count Start Other Con 0 0 39.00 92 12 25 0.00 2 1 365 1 0 0 0 0 0 38.34 92 162 0 3 21 2 1 0 2 0 7 9 3 79.00 113 0 0 0 38.40 92 25 17 2 13 21 5 43.16 52 0 5 97 11 0 15 1 35.97 0 0 7 6 96 94 0 0 6 7 2 67 13.43 70 70 0 0 42 427 143.76 174 37 28 3 8 730 6 2 2 9 199.00 28771 8 6 3 2 1 2 8 98.58 2 10 564 1 0 0 54 70 11 13.69 366 0 0 0 0 0 37 66 8 2 12 39.50 91 0 5 22 2 0 0 13 0.00 29136 0 0 11 13 14 0.00 365 3 2 0 0 21 24 0 0 0 15 65.94 286 0 0 69 33 22.76 0 0 0 16 365 0 0 45 43 0 17 9.59 731 0 0 0 0 8 6 199.00 23 7 2 18 28775 5 3 3 3 19 35.97 95 0 0 0 0 0 6 15 0.00 3 2 2 20 366 1 11 6 35.97 0 0 21 274 3 1 1 0 0 38.89 4 4 7 22 94 19 11 2 39 23 39.00 95 79 56 1 38 1 18 24 0.00 182 17 0 0 0 0 0 0 6 6 0 2 25 50.63 183 0 15 19 199.00 28789 26 6 1 0 0 0 3 27 40.18 0 0 0 0 0 2 3 181 0.00 4 28 29083 0 0 0 0 0 8 29 65.94 184 38 3 0 3 0 51 59 1 0 0 25261 0.00 29238 0 0 0 0 8 4 2 3 25262 35.97 91 1 0 0 25263 4 0 216.66 28767 60 12 6 1 0 25264 0.00 181 38 16 0 16 0 0 0 0 25265 79.00 275 6 5 0 1 0 0 210.94 2 0 0 0 25266 28781 0 0 25267 9 0 2 0 35.97 274 8 0 0 0 0 0 25268 16.88 92 19 0 0 0 25269 0.00 174 0 0 0 0 0 0 0 25270 79.00 0 0 0 0 0 273 0 0 25271 2 2 0 0.00 417 1 0 0 0 25272 174.90 20 365 14 5 1 0 0 25273 54.45 92 0 0 0 0 0 0 1 25274 33.58 184 0 0 0 0 0 0 0 25275 0.00 182 0 0 25276 19.63 31 0 0 0 79.00 9 0 25277 274 4 0 1 0 0 25278 0.00 731 0 0 0 0 0 0 0 12 0 0 25279 0.00 365 0 0 0 0 39.16 7 0 0 0 0 25280 92 0 0 25281 35.97 366 5 4 0 2 0 0 0 39.00 0 25282 91 5 0 0 0 25283 212.13 28791 6 0 0 0 0 0 0 25284 35.97 92 16 10 0 0 0 25285 35.97 183 4 0 0 0 0 0 0 40 0 25286 19.63 0 0 0 0 0 31 25287 212.13 28781 6 2 0 2 0 0 25288 0.00 92 0 0 0 0 0 0 0 25289 48.36 299 1 0 0 0 0 0 0 0 0 0 0 25290 12.40 93 0 0 25291 rows × 44 columns In [6]:  $sse = {}$ for k in range (1, 20): km = KMeans(n\_clusters = k, max\_iter = 100) sse[k] = km.inertia\_ df = pd.DataFrame({"k":list(sse.keys()), "sse":list(sse.values())}) In [7]: ggplot(df, aes(x = 'k', y = 'sse')) + geom line()In [8]: 3000000000000 -20000000000000 -10000000000000 -5 10 15 k Out[8]: <ggplot: (104809909105)> In [9]: from sklearn.cluster import KMeans km = KMeans(n clusters = 4, random state = 20)km.fit(x)Out[9]: KMeans(algorithm='auto', copy\_x=True, init='k-means++', max\_iter=300, n\_clusters=4, n\_init=10, n\_jobs=None, precompute\_distances='auto', random state=20, tol=0.0001, verbose=0) In [10]: centers = km.cluster centers centers Out[10]: array([[ 4.24444229e+01, 3.62281633e+02, 2.56964898e+01, 5.67330612e+00, 1.20685714e+00, 2.57289796e+00, 2.39673469e-01, 2.95624490e+00, 4.11020408e+00, 3.49844898e+00, 4.01306122e-01, 9.79591837e-04, 5.75412245e+00, 1.67213061e+01, 6.17142857e-02, 7.90204082e-02, 2.82938776e-01, 1.28653061e-01, 6.53061224e-02, 3.82367347e-01, 1.17683641e-14, 1.00000000e+00, 6.48816327e-01, 3.51183673e-01, 8.81632653e-03, 9.91183673e-01, 8.24653061e-01, 1.75346939e-01, 9.18204082e-01, 8.17959184e-02, 5.22612245e-01, 4.77387755e-01, 1.15591837e-01, 4.15183673e-01, 4.69224490e-01, 6.00653061e-01, 3.99346939e-01, 1.25387755e-01, 3.79591837e-01, 4.95020408e-01, 5.70448980e-01, 4.29551020e-01, 3.79591837e-01, 6.20408163e-01], [ 1.88906369e+02, 2.88265564e+04, 3.92572816e+01, 1.24626587e+01, 3.71340553e+00, 5.79387603e+00, 8.51755041e-01, 3.05601195e+00, 3.45761763e+00, 2.80937267e+00, 4.67699776e-01, 1.12023898e-03, 5.02371173e+00, 1.48155340e+01, 8.31404033e-01, 8.96191187e-03, 3.93950709e-02, 2.33383122e-02, 9.14861837e-03, 8.77520538e-02, 1.00000000e+00, 1.02362563e-13, 1.00000000e+00, 4.99600361e-15, 3.73412995e-04, 9.99626587e-01, 7.94996266e-01, 2.05003734e-01, 9.16168783e-01, 8.38312173e-02, 9.99253174e-01, 7.46825990e-04, 5.95593727e-02, 4.66952950e-01, 4.73487677e-01, 5.48730396e-01, 4.51269604e-01, 1.71209858e-01, 4.40253921e-01, 3.88536221e-01, 5.39395071e-01, 4.60604929e-01, 4.40440627e-01, 5.59559373e-01], [ 3.16945211e+01, 1.28312834e+02, 2.44217916e+01, 4.02291128e+00, 1.09336779e+00, 1.96425495e+00, 1.98449612e-01, 2.51283376e+00, 3.22101637e+00, 2.66511628e+00, 5.05943152e-01, 2.58397933e-04, 4.33514212e+00, 1.32403101e+01, 1.72265289e-04, 8.80275624e-02, 2.85271318e-01, 1.36175711e-01, 7.23514212e-02, 4.18001723e-01, -2.42306175e-14, 1.00000000e+00, 8.74677003e-01, 1.25322997e-01, 6.63221361e-03, 9.93367786e-01, 8.28768303e-01, 1.71231697e-01, 8.67441860e-01, 1.32558140e-01, 6.93453919e-01, 3.06546081e-01, 1.27906977e-01, 4.91559001e-01, 3.80534022e-01, 5.32558140e-01, 4.67441860e-01, 1.14642550e-01, 4.59517657e-01, 4.25839793e-01, 6.69078381e-01, 3.30921619e-01, 4.59603790e-01, 5.40396210e-01], [ 6.08876727e+01, 7.08873182e+02, 8.05681818e+00, 3.17045455e+00, 8.08636364e-01, 1.11727273e+00, 1.41363636e-01, 4.35090909e+00, 4.60909091e+00, 4.81954545e+00, 4.51363636e-01, -5.96311195e-18, 7.82409091e+00, 2.20550000e+01, 8.95454545e-02, 3.90909091e-02, 1.68636364e-01, 1.14090909e-01, 5.59090909e-02, 5.32727273e-01, 4.21884749e-15, 1.00000000e+00, 7.75454545e-01, 2.24545455e-01, 1.81818182e-03, 9.98181818e-01, 8.35454545e-01, 1.64545455e-01, 9.61363636e-01, 3.86363636e-02, 2.56363636e-01, 7.43636364e-01, 2.25000000e-01, 4.18181818e-01, 3.56818182e-01, 5.35000000e-01, 4.65000000e-01, 1.22727273e-01, 4.00909091e-01, 4.76363636e-01, 5.71818182e-01, 4.28181818e-01, 4.00909091e-01, 5.99090909e-01]]) In [11]: labels = km.labels In [12]: labels array([2, 0, 2, ..., 2, 0, 2])Out[12]: In [13]: web['Customer Type All'] = labels In [14]: ggplot(web, aes(x = 'PCA\_X', y = 'PCA\_Y', color = 'factor(Customer\_Type\_All)')) + geom\_point() 0.5 factor(Customer Type All) 0 --0.5 --0.50.5 PCA X Out[14]: <ggplot: (-9223371932045234446)> K-means Off PCA In [15]: x = web.iloc[:, 46:59]Out[15]: PCA1 PCA2 PCA3 PCA4 PCA5 PCA6 PCA7 PCA8 PCA9 PCA<sub>10</sub> PCA11 PCA12 -0.160964 **0** -0.292194 -0.259184 0.051102 0.404735 0.204449 -0.133562 0.201701 0.446019 0.162471 -0.129026 0.239844 -0.581994 -0.139768 -0.213536 -0.072823 -0.229437 0.048782 0.170642 -0.148091 -0.162538 0.114197 0.174945 0.414098 **2** -0.620542 -0.015141 0.045022 0.546917 -0.374148 -0.004509 0.103327 -0.181328 0.180809 0.050306 -0.016210 0.158139 -0.394892 -0.107622 0.409122 0.471256 -0.283308 0.417196 0.065522 -0.216234 -0.063017 -0.102674 -0.021113 0.097575 0.035455 -0.604825 -0.137909 0.351037 0.505756 0.122261 -0.235885 0.246212 0.078763 0.081814 -0.117303 0.318768 -0.406194 -0.263317 0.069380 -0.281943 0.595067 -0.132133 0.444822 -0.227996 0.134130 0.057659 -0.121977 -0.079076 -0.632558 -0.241098 -0.200424-0.098260 -0.104463 -0.3726990.039199 0.314547 -0.311037 0.284199 -0.268615 -0.031236 **7** -0.318732 -0.113650 0.271210 -0.002947 0.318741 0.198069 0.312144 -0.128673 0.023695 0.444019 0.217103 0.514205 **8** -0.557176 -0.221933 -0.066711 0.124488 0.174524 -0.253228 -0.124174 -0.295338 0.113846 0.406456 0.442413 -0.071950 0.620678 -0.408794 0.213353 -0.015088 -0.562990 0.006194 0.143243 0.003673 -0.160492 0.149628 -0.316220 -0.000159 -0.386065 -0.081742 0.156316 0.010644 0.339787 -0.006374 0.327659 -0.123174 -0.051739 0.317886 0.274534 0.587941 -0.360746 -0.113544 0.194980 0.217348 0.363409 0.003649 0.405244 -0.137255 -0.091587 0.312968 0.226179 0.505463 0.200497 12 -0.554453 -0.013881 0.093560 0.541658 -0.077807 0.041825 -0.004523 0.113836 -0.113151 0.545739 0.238467 -0.567497 0.362141 0.124027 0.487763 -0.237739 -0.023579 0.158606 -0.201522 -0.122383 -0.116378 0.035101 0.243303 **14** -0.459220 -0.133786 -0.211971 -0.0051220.083364 0.188527 0.416789 0.379960 -0.118115 0.113671 0.061498 0.479427 **16** -0.347642 -0.085939 -0.063341 0.225121 0.084637 0.419107 0.154759 0.383246 -0.138697 -0.138538 0.353463 0.506566 17 -0.371320 -0.181434 -0.270214 0.018069 0.302051 0.188306 0.454039 0.479881 -0.326678 0.235092 -0.160385 0.084463 18 -0.547784 0.702008 0.235166 0.426912 -0.069474 -0.069197 -0.049622 -0.029303 0.035672 -0.125911 -0.031102 0.002813 19 -0.391643 -0.292090 0.067772 -0.272968 0.626424 -0.124848 0.479744 -0.235544 0.011345 -0.046162 -0.088146 -0.048242 -0.158003 -0.308416 20 -0.474910 -0.039721 0.022343 0.175655 0.332814 0.521864 -0.114163 0.073135 -0.0744790.292423 21 0.468748 -0.259266 0.460226 -0.123761 -0.046671 0.201677 -0.033993 0.089507 -0.017083 0.074733 0.197971 -0.398897 22 -0.632253 -0.075714 -0.209887-0.380011-0.166915 0.046953 0.351703 -0.320274 0.331344 -0.190585 -0.116134 -0.03950723 -0.411257 -0.025301 -0.065132 -0.109708 0.428809 0.156601 0.450488 -0.231203 0.384360 0.382385 -0.015494 0.161955 24 -0.610911 -0.166936 -0.339975 -0.112720 -0.170359 0.064775 -0.005479 0.605162 -0.035119 -0.171899 -0.103344 0.174710 25 -0.355159 -0.373939 0.409958 -0.131940 0.502452 0.278066 0.064770 -0.070773 -0.297325 0.345701 0.014634 0.139598 **26** -0.515606 0.678386 0.210834 0.434911 -0.084725 -0.083457 -0.094820 -0.011901 -0.092068 -0.283108 -0.037205 -0.052801 27 -0.159409 -0.040975 0.111032 -0.029339 0.039752 -0.069221 0.146080 -0.035275 0.139207 -0.143919 0.144746 -0.048860 28 -0.326686 0.315683 0.182080 0.268498 0.298285 0.098640 0.533994 0.042628 0.022300 -0.201793 -0.001625 -0.16027829 -0.425562 -0.066087 0.162608 -0.028175 0.121991 -0.026457 0.317841 -0.042052 0.045116 0.232203 0.534030 0.576543 -0.439308 0.375044 -0.128728 0.103050 0.015309 -0.165693 -0.197950 0.000654 0.064109 25261 -0.279884 -0.055941 -0.424488 25262 0.785737 -0.116550 -0.307227 0.130391 0.169334 0.044532 -0.146269 -0.086960 0.197285 0.038741 -0.035276 0.046278 25263 0.500069 0.826177 0.061576 -0.085213 0.005841 -0.024766 -0.031802 0.001751 0.059730 0.123093 -0.039125 -0.033085 25264 -0.275002 -0.340522 0.023198 -0.190629 0.148790 -0.388354 -0.379526 0.061940 0.181692 0.169076 -0.035654 -0.018940 -0.158057 25265 0.597590 0.218391 -0.089521 -0.3454940.545797 -0.009793 -0.192782 -0.094449 0.047859 -0.083208 -0.006814 0.787303 -0.025909 -0.005379 0.007955 25266 0.548100 0.046138 -0.075846 0.037217 -0.000414 -0.147063 -0.068303 -0.002521 25267 0.478708 -0.263634 0.481883 -0.128469 -0.063151 0.185765 -0.044693 0.099000 0.058595 0.004622 0.459696 -0.073066 25268 -0.410429 -0.222455-0.387532 -0.012076 0.361513 0.016363 -0.223065 0.025879 -0.184486 0.117283 -0.087152 -0.126891 25269 -0.428569 -0.136624 -0.303863 -0.089913 -0.175161 0.001717 -0.141539 0.194326 -0.016568 -0.171419 0.597806 -0.059439 0.503246 25270 -0.112327 0.206902 -0.038086 -0.093322 0.488354 -0.034585 0.067426 0.036664 -0.072432 0.489289 -0.062214 25271 0.729187 -0.351095 0.107498 -0.004469 0.207491 -0.363548 -0.139657 -0.032016 0.059669 -0.009023 -0.013340 0.048004 25272 0.628255 0.133478 0.328442 -0.145043 0.010960 -0.361495 0.027235 0.053691 0.109251 0.164287 -0.016233 -0.058406 25273 -0.322344 -0.242561 0.286743 0.613155 0.384291 -0.248470 0.095660 -0.060528 -0.198905 0.012170 -0.196041 -0.243371 -0.138556 -0.019036 25274 0.799984 -0.318437 0.135919 0.168873 0.044147 -0.150810 -0.084824 0.138635 -0.022699 0.056594 25275 0.788434 -0.181608 -0.337422 0.145448 0.165483 0.039881 -0.138242 -0.079510 0.084950 -0.074667 -0.002476 0.062613 25276 0.735731 -0.3399000.117423 -0.0088850.214679 -0.364088 -0.138399-0.034717 0.037415 -0.029250 -0.010470 0.051728 25277 0.597278 -0.158181 0.217639 -0.089475 -0.3472470.545823 -0.011307 -0.192610 -0.092963 0.048252 -0.083425 -0.007027 25278 0.729563 -0.351288 0.105824 -0.003916 0.209627 -0.362878 -0.137086 -0.032272 0.039694 -0.027910 -0.008947 0.050909 25279 0.787570 -0.177768 -0.340950 0.145691 0.158219 0.039144 -0.147382 -0.078586 0.109331 -0.056309 -0.007329 0.059590 25280 0.740388 -0.111370 -0.256200 0.038956 -0.390127 0.031545 0.179625 -0.199245 -0.091110 0.046386 -0.067359 0.017506 25281 0.565905 -0.337597 0.528359 -0.188414 -0.2887520.186787 -0.015520 -0.144415 -0.112521 0.083749 -0.081913 -0.014052 -0.253452 25282 0.740657 -0.1073900.037937 -0.391868 0.032725 0.180132 -0.200051 -0.070977 0.068530-0.072627 0.014354 25283 0.546799 0.789443 0.046350 -0.076257 0.035353 -0.026073 -0.007417 -0.000175 -0.141268 -0.063683 0.006701 -0.003336 -0.082940 25284 0.680423 -0.278599 0.174282 -0.100953 -0.318054-0.361011 0.151601 -0.143953 -0.060242 0.143411 0.000102 0.056316 25285 0.567574 -0.342981 0.523015 -0.186327 -0.285158 0.185362 -0.013115 -0.144113 -0.138741 -0.075224 -0.009809 -0.419422 -0.214782 -0.388284 -0.013407 25286 0.349196 0.015291 -0.235213 0.027728 -0.147909 0.145897 -0.094488 -0.131949 -0.077291 -0.025572 25287 0.545645 0.795293 0.048695 0.033628 -0.008930 0.000007 -0.122602 -0.044448 0.002204 -0.006425 -0.149529 25288 0.655628 -0.111970 -0.228576 0.074228 -0.100203 0.102681 0.228435 0.515715 0.079255 -0.107564 0.117096 -0.132038 -0.312521 0.179185 -0.143977 -0.007400 25289 0.805763 0.133214 0.043512 -0.087241 0.078191 -0.078526 0.065319 -0.144387 -0.363790 0.167062 -0.204512 25290 -0.292134-0.3224240.028377 -0.064911 0.418593 0.574917 -0.027687 -0.146544 25291 rows × 13 columns In [16]: | sse = {} for k in range (1, 20): km = KMeans(n clusters = k, max\_iter = 100) km.fit(x)sse[k] = km.inertiadf = pd.DataFrame(("k":list(sse.keys()), "sse":list(sse.values()))) In [17]: In [18]: |ggplot(df, aes(x = 'k', y = 'sse')) + geom line()20000 -15000 -10000 -5000 -5 15 10 k Out[18]: <ggplot: (104809541324)> In [19]: from sklearn.cluster import KMeans km = KMeans(n\_clusters = 4, random\_state = 20) km.fit(x)Out[19]: KMeans(algorithm='auto', copy\_x=True, init='k-means++', max\_iter=300, n\_clusters=4, n\_init=10, n\_jobs=None, precompute\_distances='auto', random state=20, tol=0.0001, verbose=0) In [20]: centers = km.cluster\_centers\_ centers Out[20]: array([[ 5.46412166e-01, 7.46410136e-01, 2.79933009e-02, -6.47265309e-02, 3.57192383e-02, -2.01890980e-02, -1.15452318e-02, -4.68068259e-03, -1.16431532e-01, -4.55774711e-02, -3.57337904e-04, 3.31881369e-04, -3.69426459e-031, [ 6.70271964e-01, -1.82410917e-01, 3.05078662e-03, 6.44100844e-03, -3.49690624e-02, 5.90262888e-03, -9.15155906e-03, 5.91598136e-03, 3.62340017e-02, 3.92631471e-03, 5.28147873e-03, 1.53171709e-03, 5.09297107e-03], [-4.86829650e-01, -1.77981508e-01, -2.09985574e-02, 1.11297102e-02, 1.53693123e-02, 6.44982658e-03, 2.16787053e-02, -1.35840945e-03, -1.42274484e-02, -3.56077875e-03, 3.44911728e-03, -2.40672357e-03, -1.22970509e-03], [-4.88710355e-01, 6.11129520e-01, 4.92925179e-02, -9.79703618e-03, 1.30948364e-02, -2.55350936e-02, -4.74328782e-02, -8.02524694e-03, 4.25895562e-02, 3.83092005e-02, -2.79570267e-02, 4.54194939e-03, -6.94333441e-03]]) In [21]: labels = km.labels In [22]: labels Out[22]: array([2, 2, 2, ..., 1, 1, 2]) In [23]: web['Customer\_Type\_PCA'] = labels In [24]: ggplot(web, aes(x = 'PCA\_X', y = 'PCA\_Y', color = 'factor(Customer\_Type\_PCA)')) + geom\_point() 0.5 factor(Customer Type PCA) • 1 2 -0.5 --0.5 0.5 0 PCA\_X Out[24]: <ggplot: (104809943816)> In [25]: web.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 25291 entries, 0 to 25290 Data columns (total 73 columns): Purchase\_Amounts 25291 non-null float64 Duration 25291 non-null int64 Send Count 25291 non-null int64 Open\_Count 25291 non-null int64 Click\_Count 25291 non-null int64 Unique\_Open\_Count 25291 non-null int64 Unique Click Count 25291 non-null int64 Start 25291 non-null int64 Other 25291 non-null int64 Completed 25291 non-null int64 NULL 25291 non-null int64 Onboarding 25291 non-null int64 App Launch Times 25291 non-null int64 Total\_Time\_Launched 25291 non-null int64 25291 non-null float64 Language\_ALL 25291 non-null float64 Language\_ENG 25291 non-null float64 Language\_ESP 25291 non-null float64 Language FRA Language\_ITA 25291 non-null float64 25291 non-null float64 Language\_Other Subscription\_Type\_Lifetime 25291 non-null float64 Subscription\_Type\_Limited 25291 non-null float64 Subscription\_Event\_Type\_INITIAL\_PURCHASE 25291 non-null float64 25291 non-null float64 Subscription\_Event\_Type\_RENEWAL 25291 non-null float64 Purchase\_Store\_App 25291 non-null float64 Purchase Store Web Demo User No 25291 non-null float64 Demo\_User\_Yes 25291 non-null float64 Free\_Trial\_User\_No 25291 non-null float64 Free\_Trial\_User\_Yes 25291 non-null float64 Auto\_Renew\_Off 25291 non-null float64 25291 non-null float64 Auto\_Renew\_On 25291 non-null float64 Country\_Europe Country\_Other 25291 non-null float64 25291 non-null float64 Country\_US/Canada 25291 non-null float64 User\_Type\_Consumer 25291 non-null float64 User\_Type\_Other Lead Platform App 25291 non-null float64 Lead\_Platform\_Unknown 25291 non-null float64 Lead\_Platform\_Web 25291 non-null float64 25291 non-null float64 Email\_Subscriber\_No Email\_Subscriber\_Yes 25291 non-null float64 Push\_Notifications\_No 25291 non-null float64 Push\_Notifications\_Yes 25291 non-null float64 25291 non-null float64 PCA X PCA Y 25291 non-null float64 25291 non-null float64 PCA1 25291 non-null float64 PCA2 25291 non-null float64 PCA3 25291 non-null float64 PCA4 25291 non-null float64 PCA5 25291 non-null float64 PCA6 25291 non-null float64 PCA7 PCA8 25291 non-null float64 PCA9 25291 non-null float64 PCA10 25291 non-null float64 25291 non-null float64 PCA11 PCA12 25291 non-null float64 PCA13 25291 non-null float64 25291 non-null object Language Subscription Type 25291 non-null object 25291 non-null object Subscription Event Type Purchase\_Store 25291 non-null object Demo User 25291 non-null object 25291 non-null object Free Trial User Auto Renew 25291 non-null object 25291 non-null object Country 25291 non-null object User Type 25291 non-null object Lead Platform 25291 non-null object Email Subscriber 25291 non-null object Push Notifications 25291 non-null int32 Customer Type All Customer Type PCA 25291 non-null int32 dtypes: float64(46), int32(2), int64(13), object(12) memory usage: 13.9+ MB In [26]: web['Customer Type All'] = web['Customer Type All'].astype(str) web['Customer Type PCA'] = web['Customer Type PCA'].astype(str) In [27]: clean = web clean.drop(clean.iloc[:,14:59], inplace = True, axis = 1) In [28]: clean.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 25291 entries, 0 to 25290 Data columns (total 28 columns): Purchase Amounts 25291 non-null float64 25291 non-null int64 Duration Send Count 25291 non-null int64 Open Count 25291 non-null int64 25291 non-null int64 Click Count Unique Open Count 25291 non-null int64 Unique\_Click\_Count 25291 non-null int64 25291 non-null int64 Start Other 25291 non-null int64 Completed 25291 non-null int64 NULL 25291 non-null int64 25291 non-null int64 Onboarding App Launch Times 25291 non-null int64 Total Time Launched 25291 non-null int64 25291 non-null object Language Subscription\_Type 25291 non-null object Subscription\_Event\_Type 25291 non-null object Purchase\_Store 25291 non-null object 25291 non-null object Demo User 25291 non-null object Free Trial User Auto Renew 25291 non-null object 25291 non-null object Country User\_Type 25291 non-null object Lead\_Platform 25291 non-null object 25291 non-null object Email Subscriber 25291 non-null object Push Notifications Customer\_Type\_All 25291 non-null object Customer Type PCA 25291 non-null object dtypes: float64(1), int64(13), object(14) memory usage: 5.4+ MB In [29]: clean.to csv('Subscriber Information (Clean) Version 6.csv', index = False) \_\_\_\_\_\_ Traceback (most recent call last) <ipython-input-29-f506dbe25b75> in <module> ----> 1 clean.to csv('Subscriber Information (Clean) Version 6.csv', index = False) ~\Anaconda3\lib\site-packages\pandas\core\generic.py in to\_csv(self, path\_or\_buf, sep, na\_rep, float\_ format, columns, header, index, index\_label, mode, encoding, compression, quoting, quotechar, line\_te rminator, chunksize, tupleize cols, date format, doublequote, escapechar, decimal) doublequote=doublequote, 3019 escapechar=escapechar, decimal=decimal) -> 3020 formatter.save() 3021 3022 if path\_or\_buf is None: ~\Anaconda3\lib\site-packages\pandas\io\formats\csvs.py in save(self) 170 self.writer = UnicodeWriter(f, \*\*writer\_kwargs) 171 --> 172 self.\_save() 173 174 finally: ~\Anaconda3\lib\site-packages\pandas\io\formats\csvs.py in \_save(self) 286 break 287 --> 288 self.\_save\_chunk(start\_i, end\_i) 289 290 def \_save\_chunk(self, start\_i, end\_i): ~\Anaconda3\lib\site-packages\pandas\io\formats\csvs.py in \_save\_chunk(self, start\_i, end\_i) 313 314 libwriters.write\_csv\_rows(self.data, ix, self.nlevels, --> 315 self.cols, self.writer) pandas/\_libs/writers.pyx in pandas.\_libs.writers.write\_csv\_rows() OSError: [Errno 22] Invalid argument **Graphing out each segment** 



