K-Means Clustering

Let's work through an example of unsupervised learning - clustering customer data.

Goal:

When working with unsupervised learning methods, its usually important to lay out a general goal. In our case, let's attempt to find reasonable clusters of customers for marketing segmentation and study. What we end up doing with those clusters would depend **heavily** on the domain itself, in this case, marketing.

The Data

LINK: https://archive.ics.uci.edu/ml/datasets/bank+marketing (https://archive.ics.uci.edu/ml/datasets/bank+marketing)

This dataset is public available for research. The details are described in [Moro et al., 2011].

```
  [Moro et al., 2011] S. Moro, R. Laureano and P. Cortez. Using Data Mining for
Bank Direct Marketing: An Application of the CRISP-DM Methodology.
  In P. Novais et al. (Eds.), Proceedings of the European Simulation and Modelli
ng Conference - ESM'2011, pp. 117-121, Guimarães, Portugal, October, 2011. EUROS
IS.

  Available at: [pdf] http://hdl.handle.net/1822/14838
                [bib] http://www3.dsi.uminho.pt/pcortez/bib/2011-esm-1.txt
 For more information, read [Moro et al., 2011].
```

```
# bank client data:
1 - age (numeric)
2 - job : type of job (categorical: 'admin.','blue-collar','entrepreneur','house
maid','management','retired','self-employed','services','student','technicia
n','unemployed','unknown')
3 - marital : marital status (categorical: 'divorced','married','single','unknow
n'; note: 'divorced' means divorced or widowed)
4 - education (categorical: 'basic.4y','basic.6y','basic.9y','high.school','illi
terate','professional.course','university.degree','unknown')
5 - default: has credit in default? (categorical: 'no','yes','unknown')
6 - housing: has housing loan? (categorical: 'no','yes','unknown')
7 - loan: has personal loan? (categorical: 'no','yes','unknown')
# related with the last contact of the current campaign:
8 - contact: contact communication type (categorical: 'cellular','telephone')
9 - month: last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'n
ov', 'dec')
10 - day_of_week: last contact day of the week (categorical: 'mon','tue','we
d','thu','fri')
11 - duration: last contact duration, in seconds (numeric). Important note: this
attribute highly affects the output target (e.g., if duration=0 then y='no'). Ye
t, the duration is not known before a call is performed. Also, after the end of
the call y is obviously known. Thus, this input should only be included for benc
hmark purposes and should be discarded if the intention is to have a realistic p
redictive model.
# other attributes:
12 - campaign: number of contacts performed during this campaign and for this cl
ient (numeric, includes last contact)
13 - pdays: number of days that passed by after the client was last contacted fr
om a previous campaign (numeric; 999 means client was not previously contacted)
14 - previous: number of contacts performed before this campaign and for this cl
ient (numeric)
15 - poutcome: outcome of the previous marketing campaign (categorical: 'failur
e','nonexistent','success')
# social and economic context attributes
16 - emp.var.rate: employment variation rate - quarterly indicator (numeric)
17 - cons.price.idx: consumer price index - monthly indicator (numeric)
18 - cons.conf.idx: consumer confidence index - monthly indicator (numeric)
19 - euribor3m: euribor 3 month rate - daily indicator (numeric)
20 - nr.employed: number of employees - quarterly indicator (numeric)
21 - y - has the client subscribed a term deposit? (binary: 'yes','no')
```

Imports

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Exploratory Data Analysis

In [2]:

```
df = pd.read_csv("D:\\Study\\Programming\\python\\Python course from udemy\\Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\22 - K-Means Clustering\\32407452-bank-full.csv")
```

In [3]:

```
df.head()
```

Out[3]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_we
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	m
1	57	services	married	high.school	unknown	no	no	telephone	may	m
2	37	services	married	high.school	no	yes	no	telephone	may	m
3	40	admin.	married	basic.6y	no	no	no	telephone	may	m
4	56	services	married	high.school	no	no	yes	telephone	may	m

5 rows × 21 columns

In [4]:

```
df.columns
```

Out[4]:

```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed', 'subscribed'],
      dtype='object')
```

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             41188 non-null  int64  
 1   job             41188 non-null  object 
 2   marital         41188 non-null  object 
 3   education       41188 non-null  object 
 4   default         41188 non-null  object 
 5   housing         41188 non-null  object 
 6   loan            41188 non-null  object 
 7   contact         41188 non-null  object 
 8   month           41188 non-null  object 
 9   day_of_week     41188 non-null  object 
 10  duration        41188 non-null  int64  
 11  campaign        41188 non-null  int64  
 12  pdays           41188 non-null  int64  
 13  previous        41188 non-null  int64  
 14  poutcome        41188 non-null  object 
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  subscribed      41188 non-null  object 
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

In [6]:

```
df.describe()
```

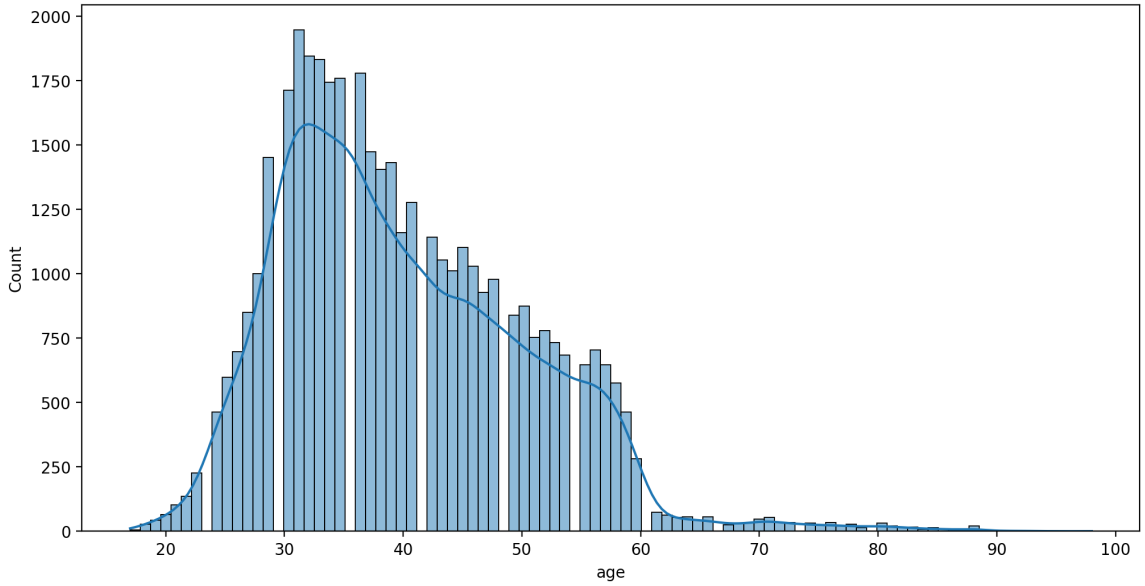
Out[6]:

	age	duration	campaign	pdays	previous	emp.var.rate	cc
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	4
mean	40.02406	258.285010	2.567593	962.475454	0.172963	0.081886	
std	10.42125	259.279249	2.770014	186.910907	0.494901	1.570960	
min	17.00000	0.000000	1.000000	0.000000	0.000000	-3.400000	
25%	32.00000	102.000000	1.000000	999.000000	0.000000	-1.800000	
50%	38.00000	180.000000	2.000000	999.000000	0.000000	1.100000	
75%	47.00000	319.000000	3.000000	999.000000	0.000000	1.400000	
max	98.00000	4918.000000	56.000000	999.000000	7.000000	1.400000	

Continuous Feature Analysis

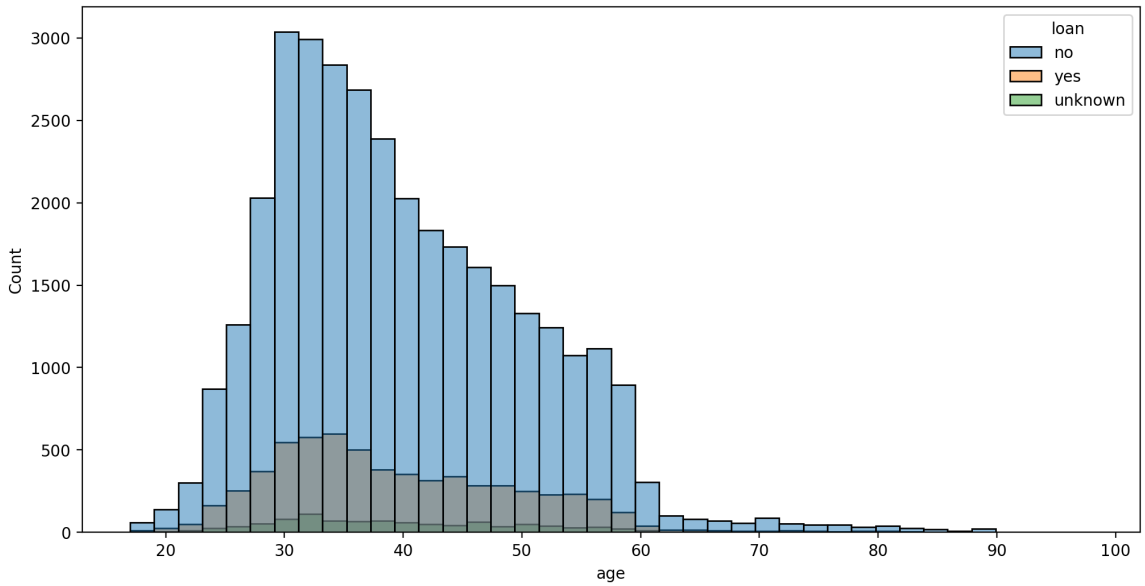
In [11]:

```
plt.figure(figsize=(12,6),dpi=200)
sns.histplot(data=df,x='age',kde=True);
```



In [14]:

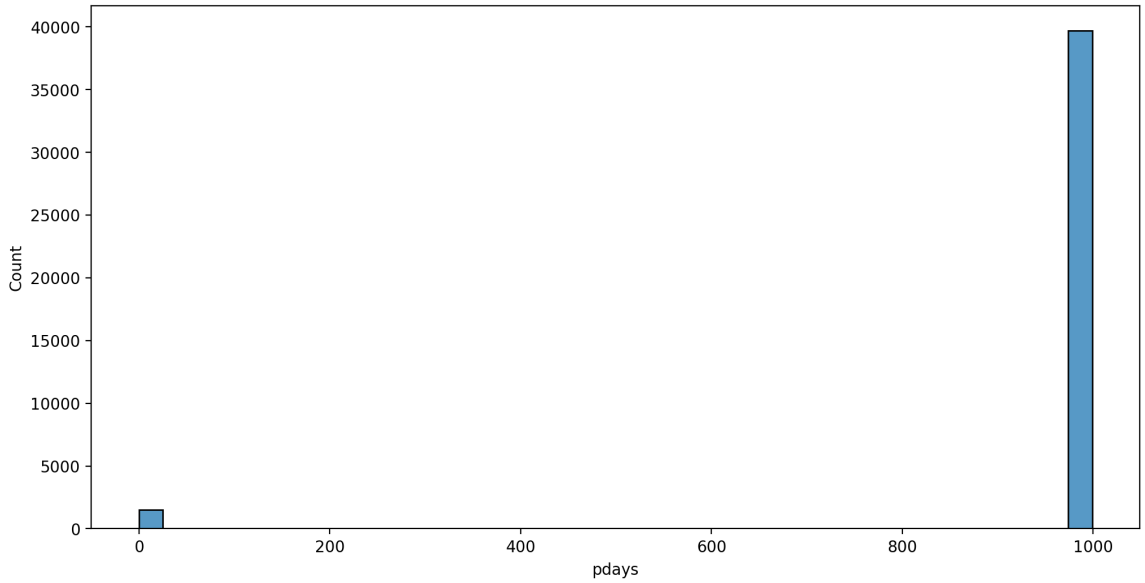
```
plt.figure(figsize=(12,6),dpi=200)
sns.histplot(data=df,x='age',bins=40,hue='loan');
```



Here pday is how many days before person is contacted like 5 days me person contact 5 days ago , 999 means person is never been contacted

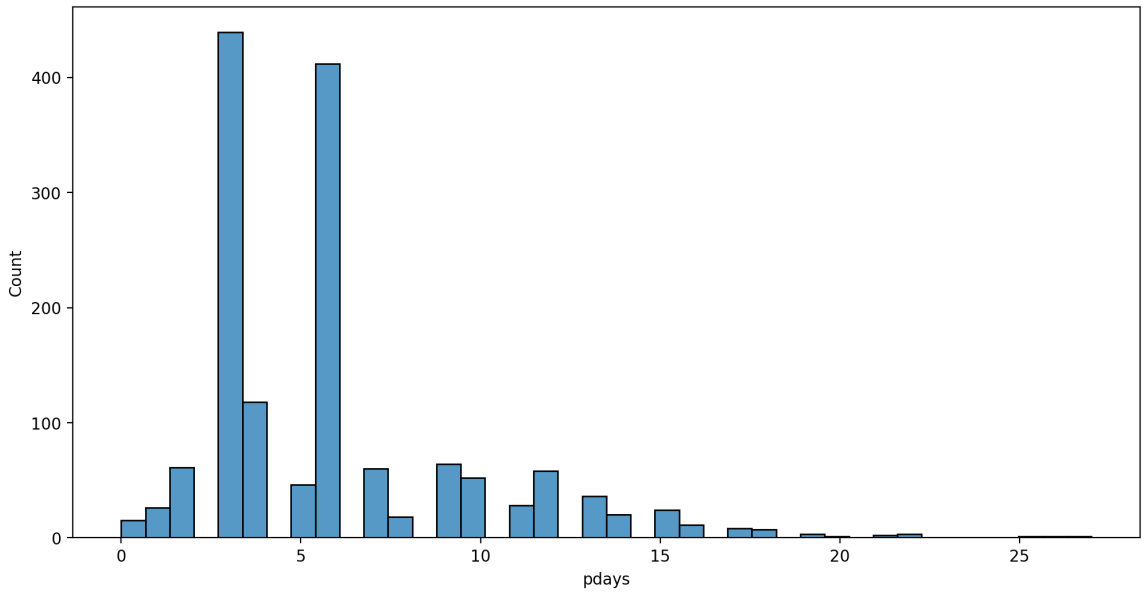
In [15]:

```
plt.figure(figsize=(12,6),dpi=200)
sns.histplot(data=df,x='pdays',bins=40);
```



In [17]:

```
plt.figure(figsize=(12,6),dpi=200)
sns.histplot(x='pdays',data=df[df['pdays']!=999],bins=40);
```



In [18]:

```
df['contact'].unique()
```

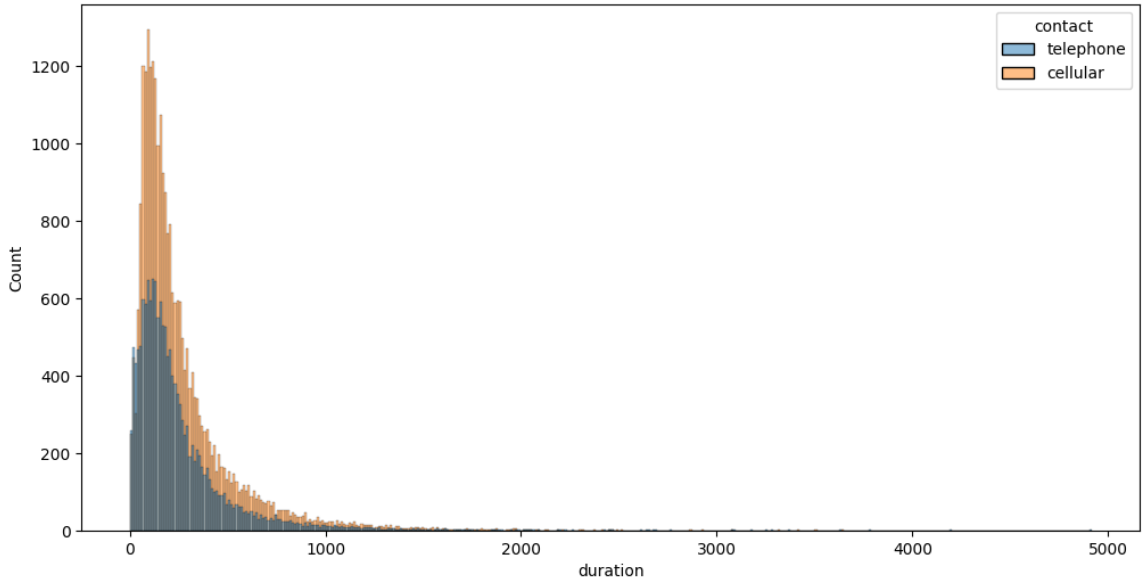
Out[18]:

```
array(['telephone', 'cellular'], dtype=object)
```

Contact duration - contact with customer made, how long did call last?

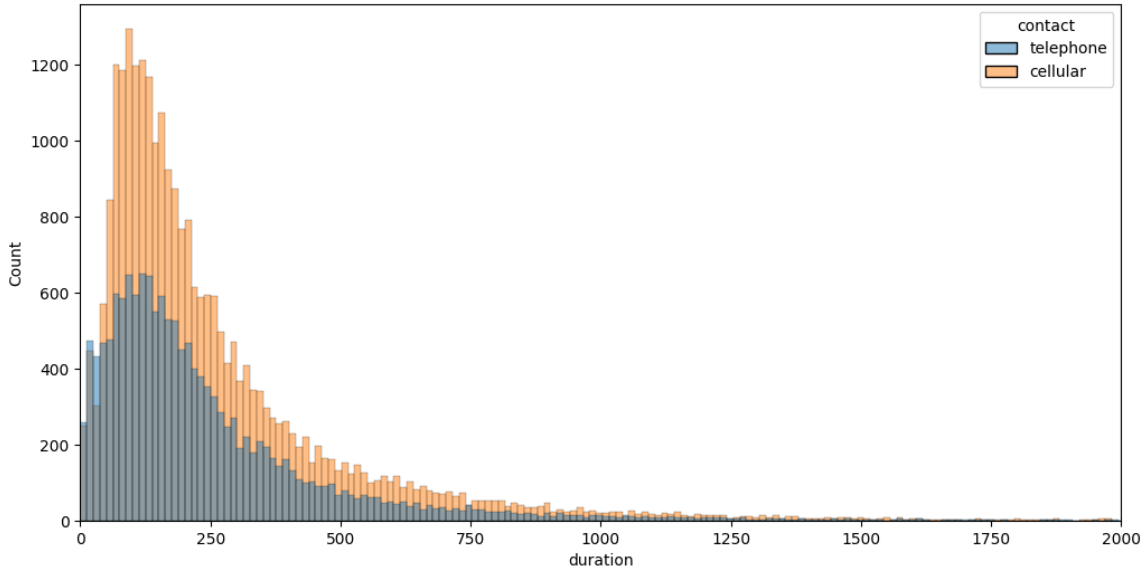
In [21]:

```
plt.figure(figsize=(12,6),dpi=100)
sns.histplot(data=df,x='duration',hue='contact');
```



In [23]:

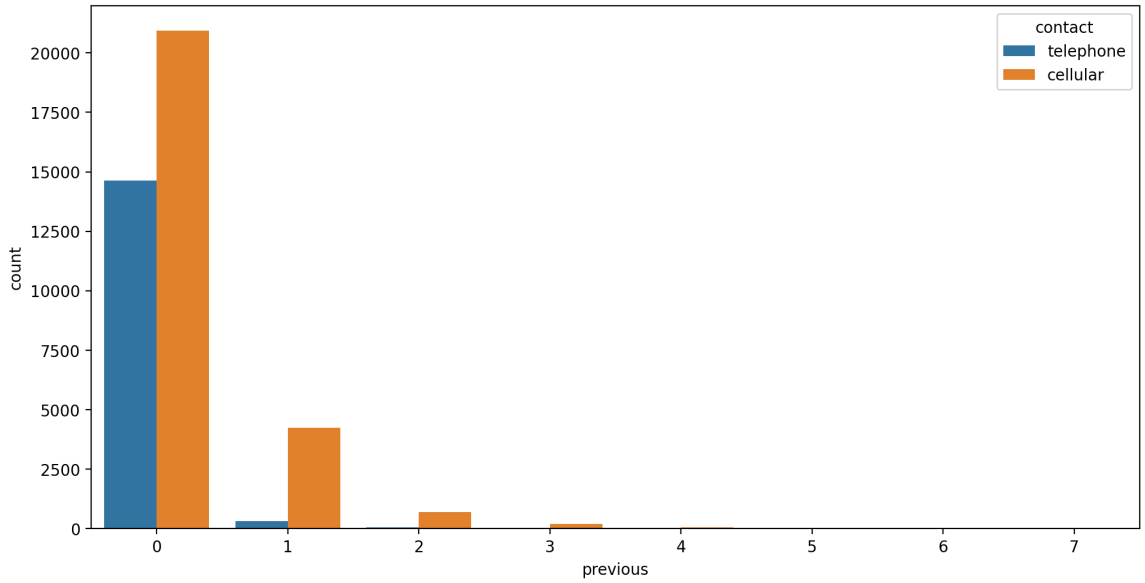
```
plt.figure(figsize=(12,6),dpi=100)
sns.histplot(data=df,x='duration',hue='contact')
plt.xlim(0,2000);
```



- 15 - previous: number of contacts performed before this campaign and for this client (numeric)
- 16 - poutcome: outcome of the previous marketing campaign (categorical: "unknown","other","failure","success"

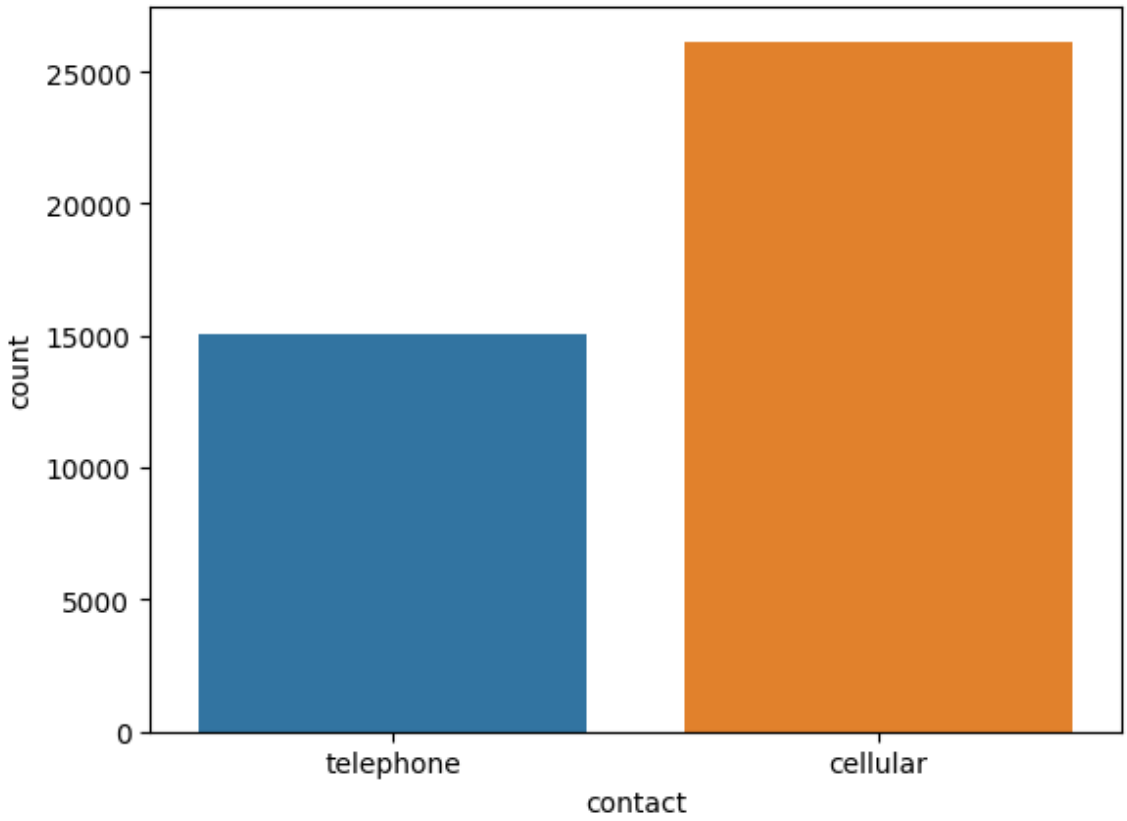
In [27]:

```
plt.figure(figsize=(12,6),dpi=200)
sns.countplot(data=df,x='previous',hue='contact');
```



In [25]:

```
sns.countplot(data=df,x='contact');
```



In [28]:

```
df['previous'].value_counts()
```

Out[28]:

```
0    35563
1     4561
2      754
3      216
4       70
5       18
6        5
7        1
Name: previous, dtype: int64
```

In [29]:

```
df['previous'].value_counts().sum()
```

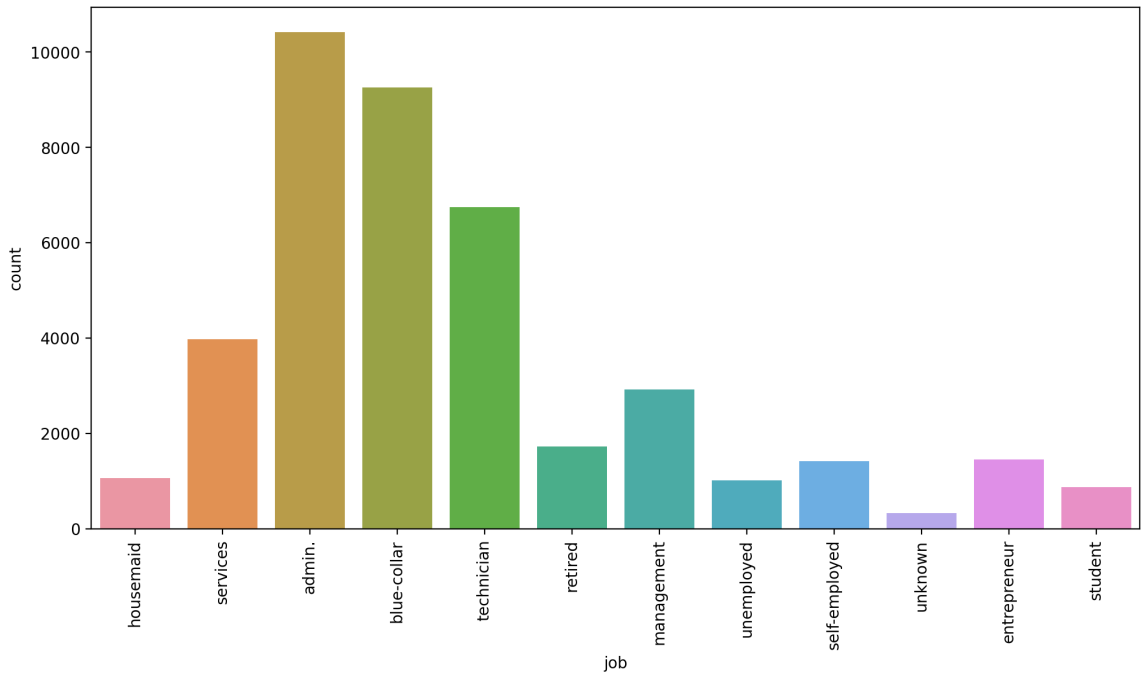
Out[29]:

```
41188
```

Categorical Features

In [33]:

```
plt.figure(figsize=(12,6),dpi=200)
sns.countplot(data=df,x='job')
plt.xticks(rotation=90);
```



In [37]:

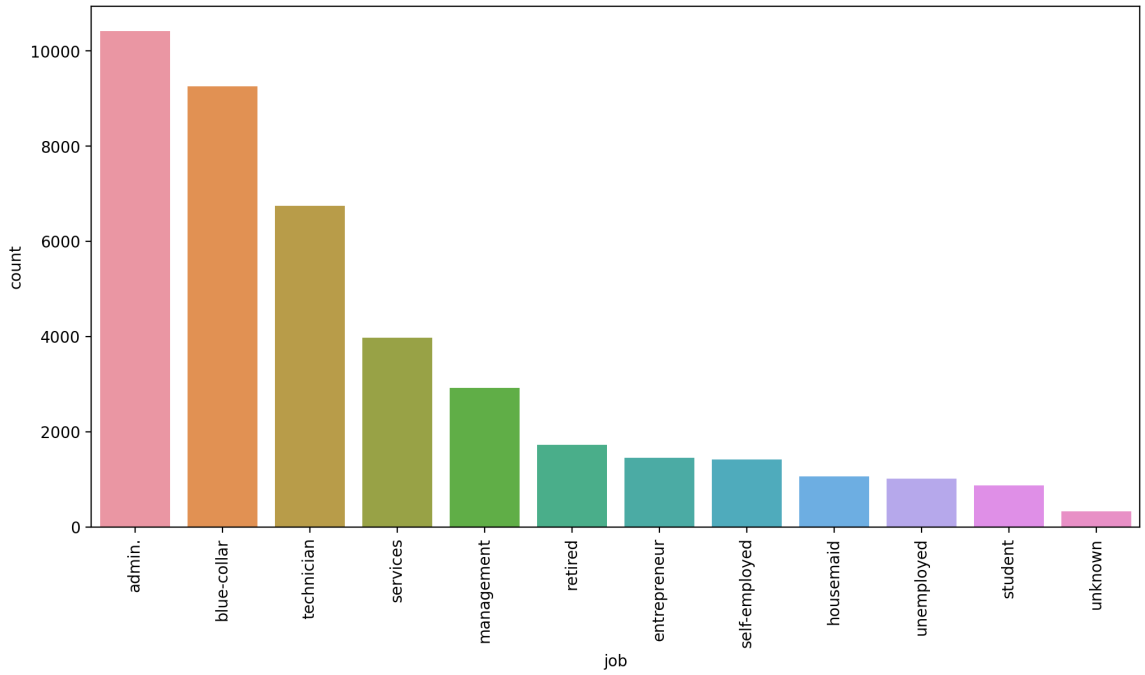
```
df['job'].value_counts().index
```

Out[37]:

```
Index(['admin.', 'blue-collar', 'technician', 'services', 'management',
       'retired', 'entrepreneur', 'self-employed', 'housemaid', 'unemploye
d',
       'student', 'unknown'],
      dtype='object')
```

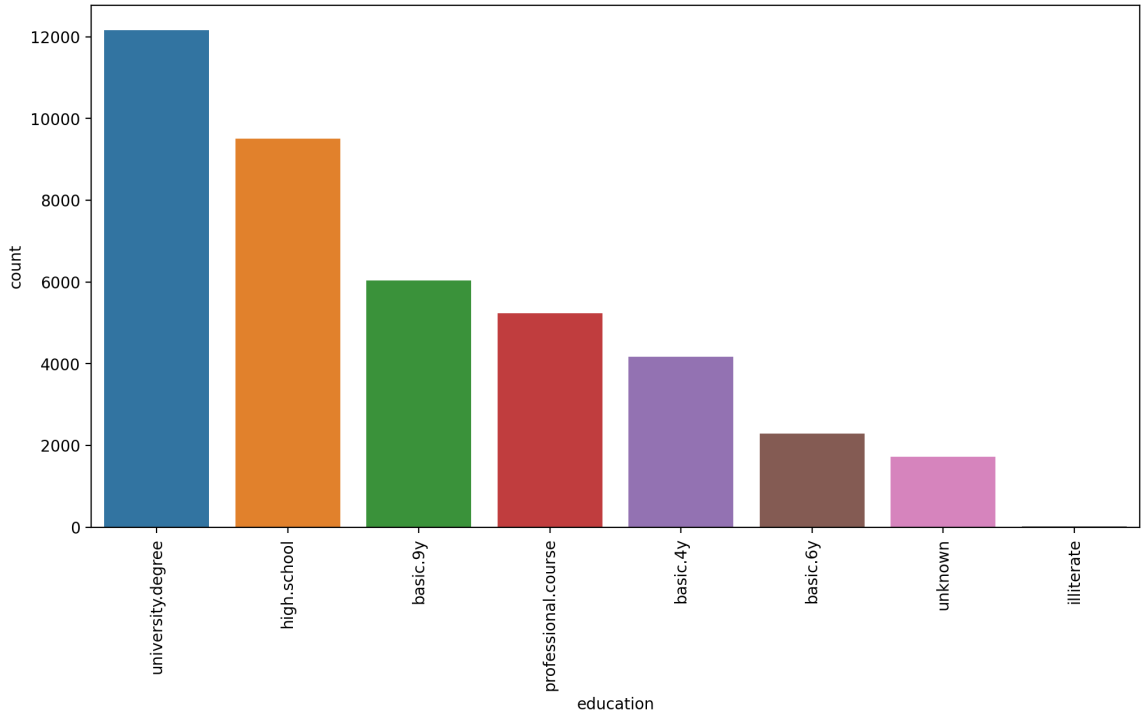
In [43]:

```
plt.figure(figsize=(12,6),dpi=200)
# https://stackoverflow.com/questions/46623583/seaborn-countplot-order-categories-by-co
unt
sns.countplot(data=df,x='job',order=df['job'].value_counts().index)
plt.xticks(rotation=90);
```



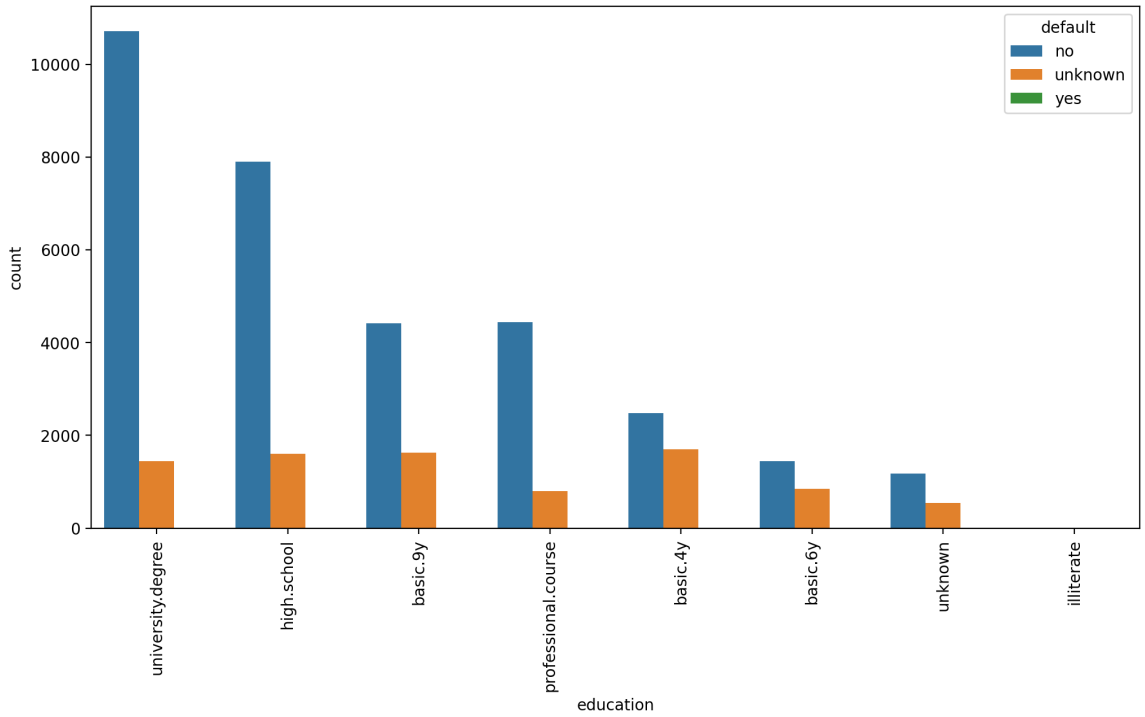
In [44]:

```
plt.figure(figsize=(12,6),dpi=200)
# https://stackoverflow.com/questions/46623583/seaborn-countplot-order-categories-by-count
sns.countplot(data=df,x='education',order=df['education'].value_counts().index)
plt.xticks(rotation=90);
```



In [45]:

```
plt.figure(figsize=(12,6),dpi=200)
# https://stackoverflow.com/questions/46623583/seaborn-countplot-order-categories-by-count
sns.countplot(data=df,x='education',order=df['education'].value_counts().index,hue='default')
plt.xticks(rotation=90);
```



In [50]:

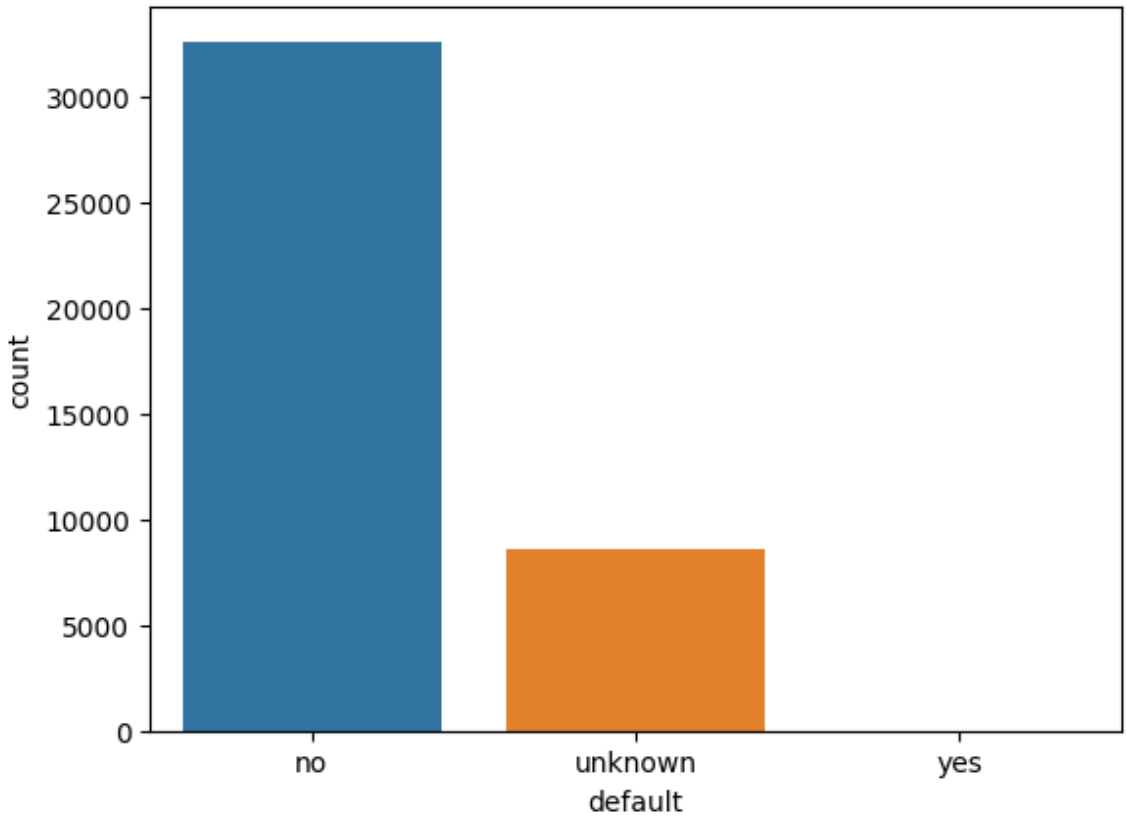
```
df['default'].value_counts()
```

Out[50]:

```
no         32588
unknown     8597
yes            3
Name: default, dtype: int64
```

In [47]:

```
sns.countplot(data=df,x='default');
```

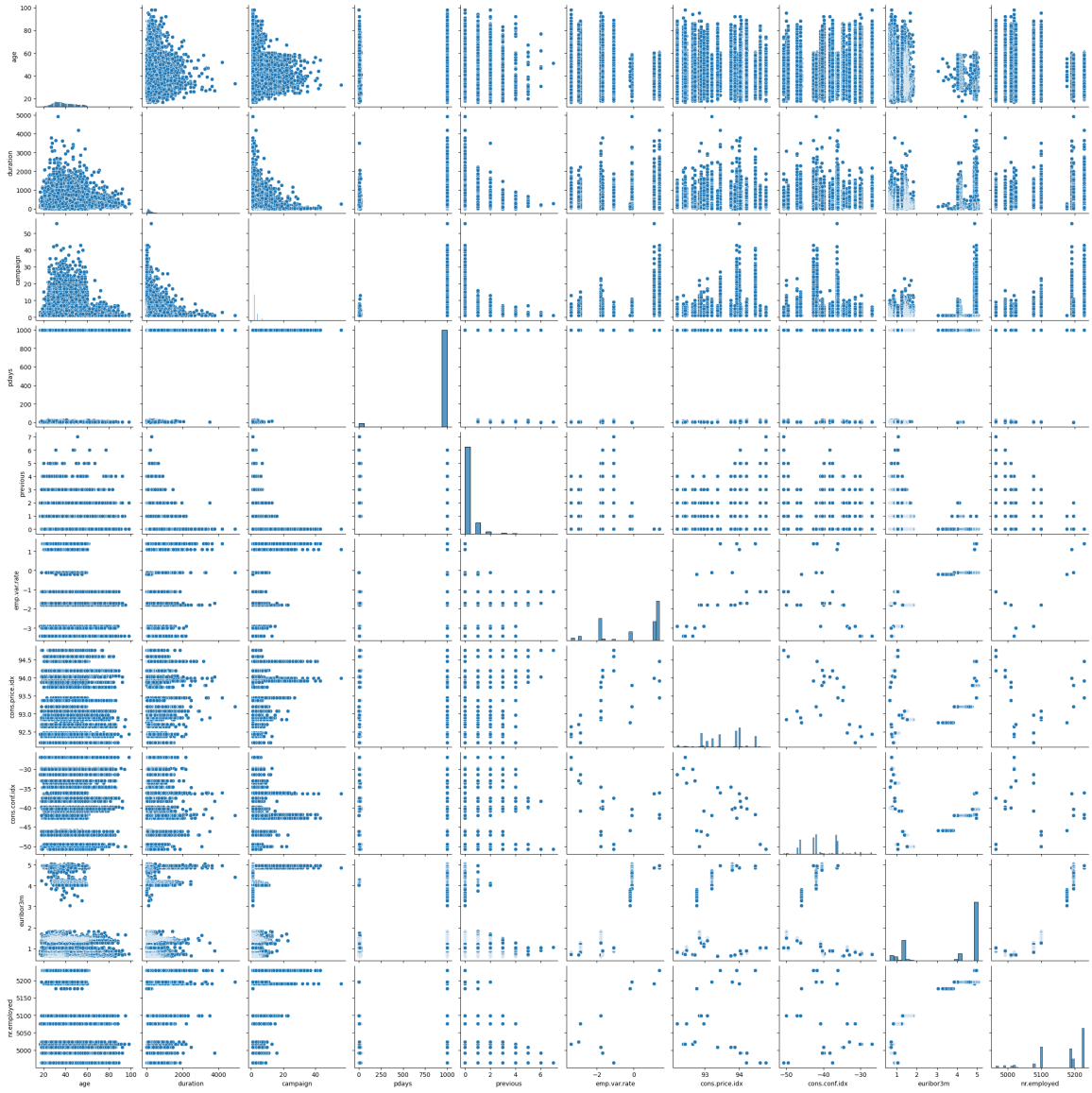


In [48]:

```
# THIS TAKES A LONG TIME!
sns.pairplot(df)
```

Out[48]:

```
<seaborn.axisgrid.PairGrid at 0x1e020ed8550>
```



Clustering

Data Preparation

UNSUPERVISED LEARNING REMINDER: NO NEED TO TRAIN TEST SPLIT!! NO LABEL TO "TEST" AGAINST!

We do however need to transform categorical features into numeric ones where it makes sense to do so, as well as scaling the data due to distance being a key factor in clustering.

In [51]:

```
df.head()
```

Out[51]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_we
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	m
1	57	services	married	high.school	unknown	no	no	telephone	may	m
2	37	services	married	high.school	no	yes	no	telephone	may	m
3	40	admin.	married	basic.6y	no	no	no	telephone	may	m
4	56	services	married	high.school	no	no	yes	telephone	may	m

5 rows × 21 columns

In [52]:

```
X = pd.get_dummies(df)
```

In [53]:

```
X.head()
```

Out[53]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euri
0	56	261	1	999	0	1.1	93.994	-36.4	
1	57	149	1	999	0	1.1	93.994	-36.4	
2	37	226	1	999	0	1.1	93.994	-36.4	
3	40	151	1	999	0	1.1	93.994	-36.4	
4	56	307	1	999	0	1.1	93.994	-36.4	

5 rows × 65 columns

In [64]:

```
from sklearn.preprocessing import StandardScaler
```

In [65]:

```
scaler = StandardScaler()
```

In [66]:

```
scaler_x = scaler.fit_transform(X)
```

Creating and Fitting a KMeans Model

Note of our method choices here:

- fit(X[, y, sample_weight])
  - Compute k-means clustering.
- fit_predict(X[, y, sample_weight])
  - Compute cluster centers and predict cluster index for each sample.
- fit_transform(X[, y, sample_weight])
  - Compute clustering and transform X to cluster-distance space.
- predict(X[, sample_weight])
  - Predict the closest cluster each sample in X belongs to.

In [67]:

```
from sklearn.cluster import KMeans
```

In [68]:

```
model = KMeans(n_clusters=2)
```

In [69]:

```
# Make sure to watch video to understand this line and fit() vs transform()
cluster_labels = model.fit_predict(scaler_x)
```

```
C:\Users\Chromsy\AppData\Roaming\Python\Python39\site-packages\sklearn\clu
ster\_kmeans.py:870: FutureWarning: The default value of `n_init` will cha
nge from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to supp
ress the warning
  warnings.warn(
```

In [132]:

```
cluster_labels # These numbers are meaning less
```

Out[132]:

```
array([1, 1, 1, ..., 0, 0, 0])
```

In [72]:

```
len(scaler_x)
```

Out[72]:

```
41188
```

In [73]:

```
len(cluster_labels)
```

Out[73]:

```
41188
```

In [74]:

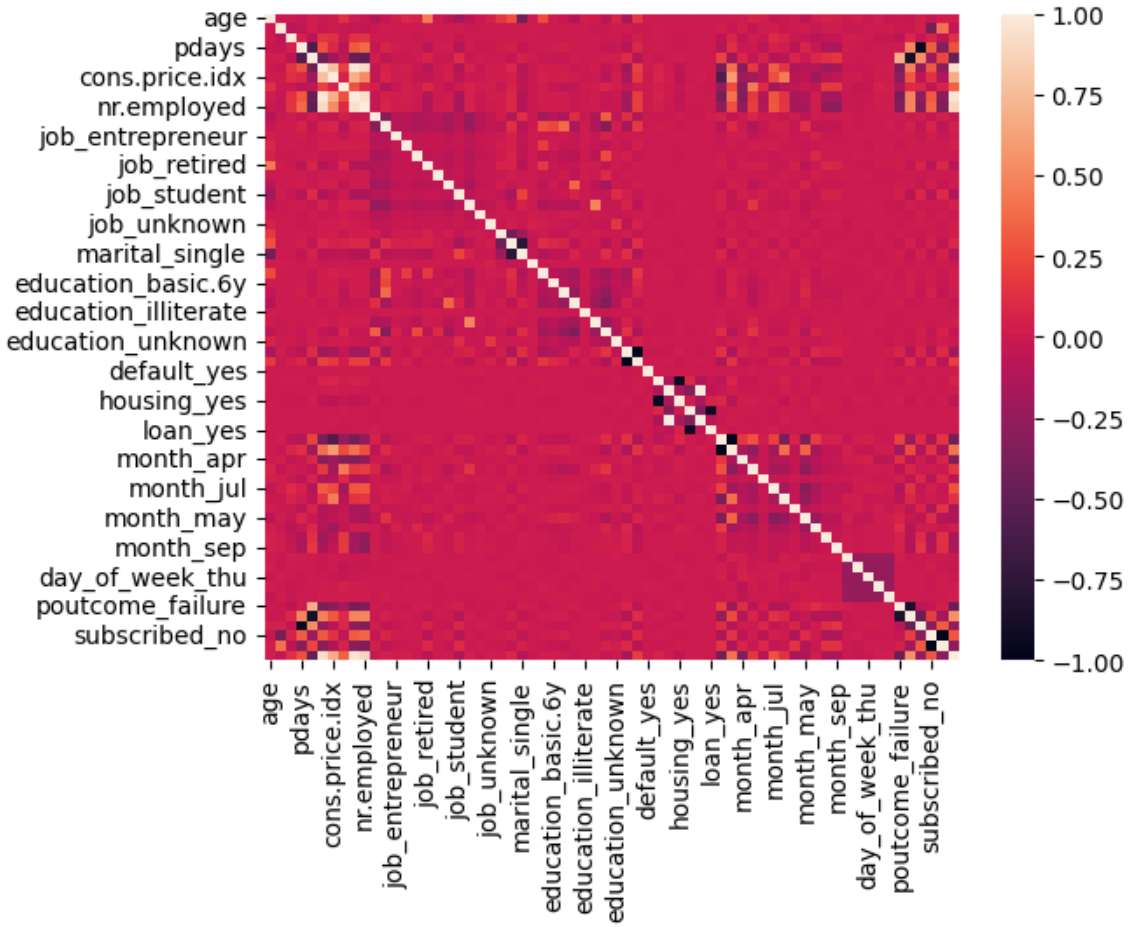
```
X['Cluster'] = cluster_labels
```

In [75]:

```
sns.heatmap(X.corr())
```

Out[75]:

```
<AxesSubplot: >
```



In [76]:

```
X.corr()['Cluster']
```

Out[76]:

```
age                    0.019699
duration              -0.039894
campaign               0.129129
pdays                  0.267700
previous              -0.478467
                           ...
poutcome_nonexistent   0.544377
poutcome_success      -0.254393
subscribed_no          0.294610
subscribed_yes        -0.294610
Cluster                1.000000
Name: Cluster, Length: 66, dtype: float64
```

In [78]:

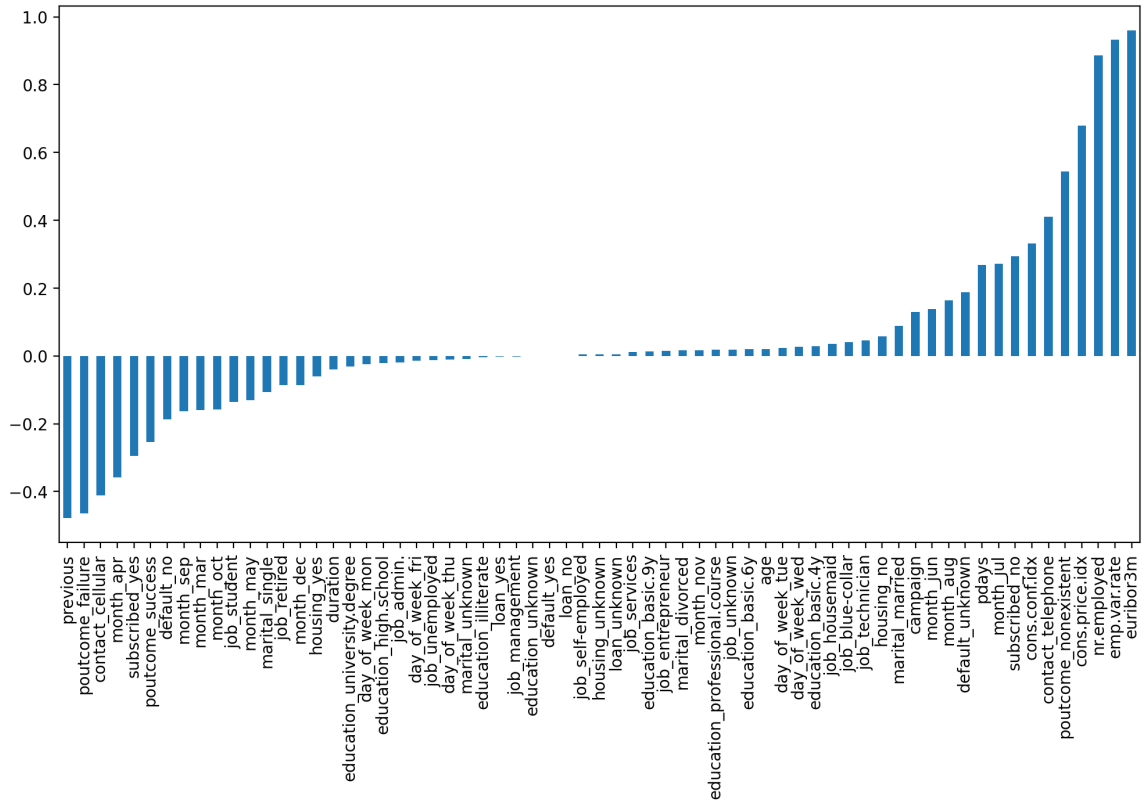
```
X.corr()['Cluster'].iloc[:-1].sort_values()
```

Out[78]:

```
previous               -0.478467
poutcome_failure       -0.464295
contact_cellular       -0.410476
month_apr              -0.357923
subscribed_yes         -0.294610
                          ...
poutcome_nonexistent    0.544377
cons.price.idx          0.679372
nr.employed             0.886155
emp.var.rate            0.932612
euribor3m               0.959297
Name: Cluster, Length: 65, dtype: float64
```

In [81]:

```
plt.figure(figsize=(12,6),dpi=200)
X.corr()['Cluster'].iloc[:-1].sort_values().plot(kind='bar');
```



Choosing K Value

In [83]:

```
ssd = []

for k in range(2,10):

    model = KMeans(n_clusters=k)
    model.fit(scaler_x)

    #Sum of squared distances of samples to their closest cluster center.
    ssd.append(model.inertia_)
```

```
C:\Users\Chromsy\AppData\Roaming\Python\Python39\site-packages\sklearn\clu
ster\_kmeans.py:870: FutureWarning: The default value of `n_init` will cha
nge from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to supp
ress the warning
  warnings.warn(
C:\Users\Chromsy\AppData\Roaming\Python\Python39\site-packages\sklearn\clu
ster\_kmeans.py:870: FutureWarning: The default value of `n_init` will cha
nge from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to supp
ress the warning
  warnings.warn(
C:\Users\Chromsy\AppData\Roaming\Python\Python39\site-packages\sklearn\clu
ster\_kmeans.py:870: FutureWarning: The default value of `n_init` will cha
nge from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to supp
ress the warning
  warnings.warn(
C:\Users\Chromsy\AppData\Roaming\Python\Python39\site-packages\sklearn\clu
ster\_kmeans.py:870: FutureWarning: The default value of `n_init` will cha
nge from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to supp
ress the warning
  warnings.warn(
C:\Users\Chromsy\AppData\Roaming\Python\Python39\site-packages\sklearn\clu
ster\_kmeans.py:870: FutureWarning: The default value of `n_init` will cha
nge from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to supp
ress the warning
  warnings.warn(
C:\Users\Chromsy\AppData\Roaming\Python\Python39\site-packages\sklearn\clu
ster\_kmeans.py:870: FutureWarning: The default value of `n_init` will cha
nge from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to supp
ress the warning
  warnings.warn(
C:\Users\Chromsy\AppData\Roaming\Python\Python39\site-packages\sklearn\clu
ster\_kmeans.py:870: FutureWarning: The default value of `n_init` will cha
nge from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to supp
ress the warning
  warnings.warn(
C:\Users\Chromsy\AppData\Roaming\Python\Python39\site-packages\sklearn\clu
ster\_kmeans.py:870: FutureWarning: The default value of `n_init` will cha
nge from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to supp
ress the warning
  warnings.warn(
```

In [88]:

```
ssd
```

Out[88]:

```
[2469792.361662749,
 2370786.7034402364,
 2271502.6970615042,
 2200694.033064819,
 2157695.047497073,
 2102832.4143065163,
 2063724.270298891,
 2036472.7042926433]
```

In [91]:

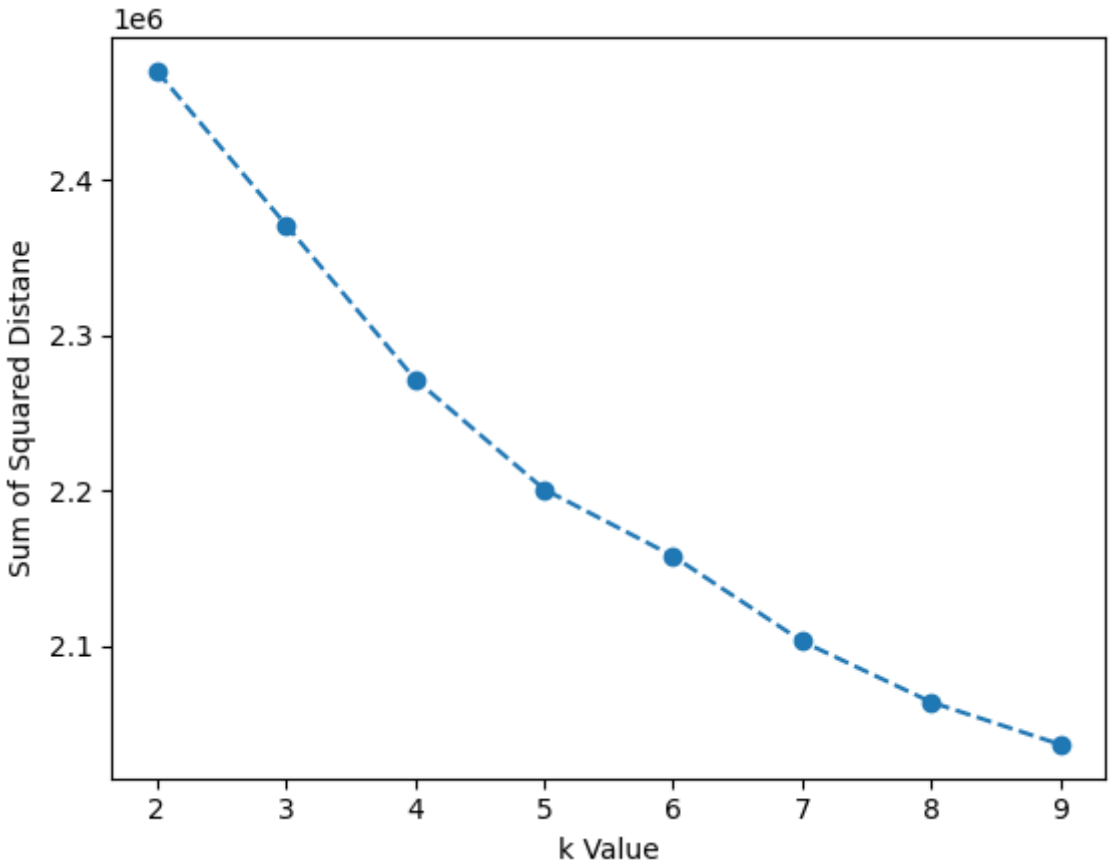
```
# Change in SSD from previous K value!
pd.Series(ssd).diff()
```

Out[91]:

```
0             NaN
1   -99005.658223
2   -99284.006379
3   -70808.663997
4   -42998.985568
5   -54862.633191
6   -39108.144008
7   -27251.566006
dtype: float64
```

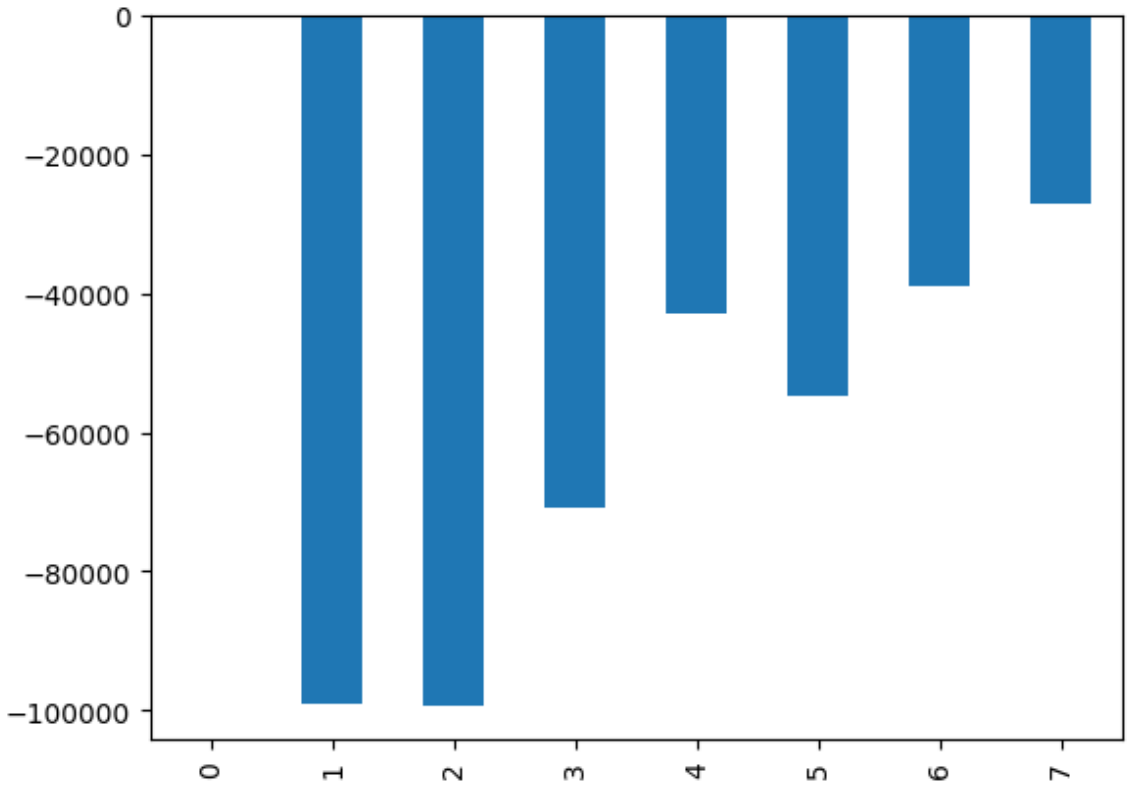
In [87]:

```
plt.plot(range(2,10),ssd,'o--')
plt.xlabel('k Value')
plt.ylabel('Sum of Squared Distane');
```



In [93]:

```
pd.Series(ssd).diff().plot(kind='bar');
```



K Means Color Quantization

Imports

In [94]:

```
import numpy as np

import matplotlib.image as mpimg
import matplotlib.pyplot as plt
```

The Image

In [95]:

```
image_as_array =mpimg.imread("D:\\Study\\Programming\\python\Python course from udemy
\\Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\22 - K-Means Clu
stering\\33555798-palm-trees.jpg")
```

In [97]:

```
image_as_array # RGB CODES FOR EACH PIXEL
```

Out[97]:

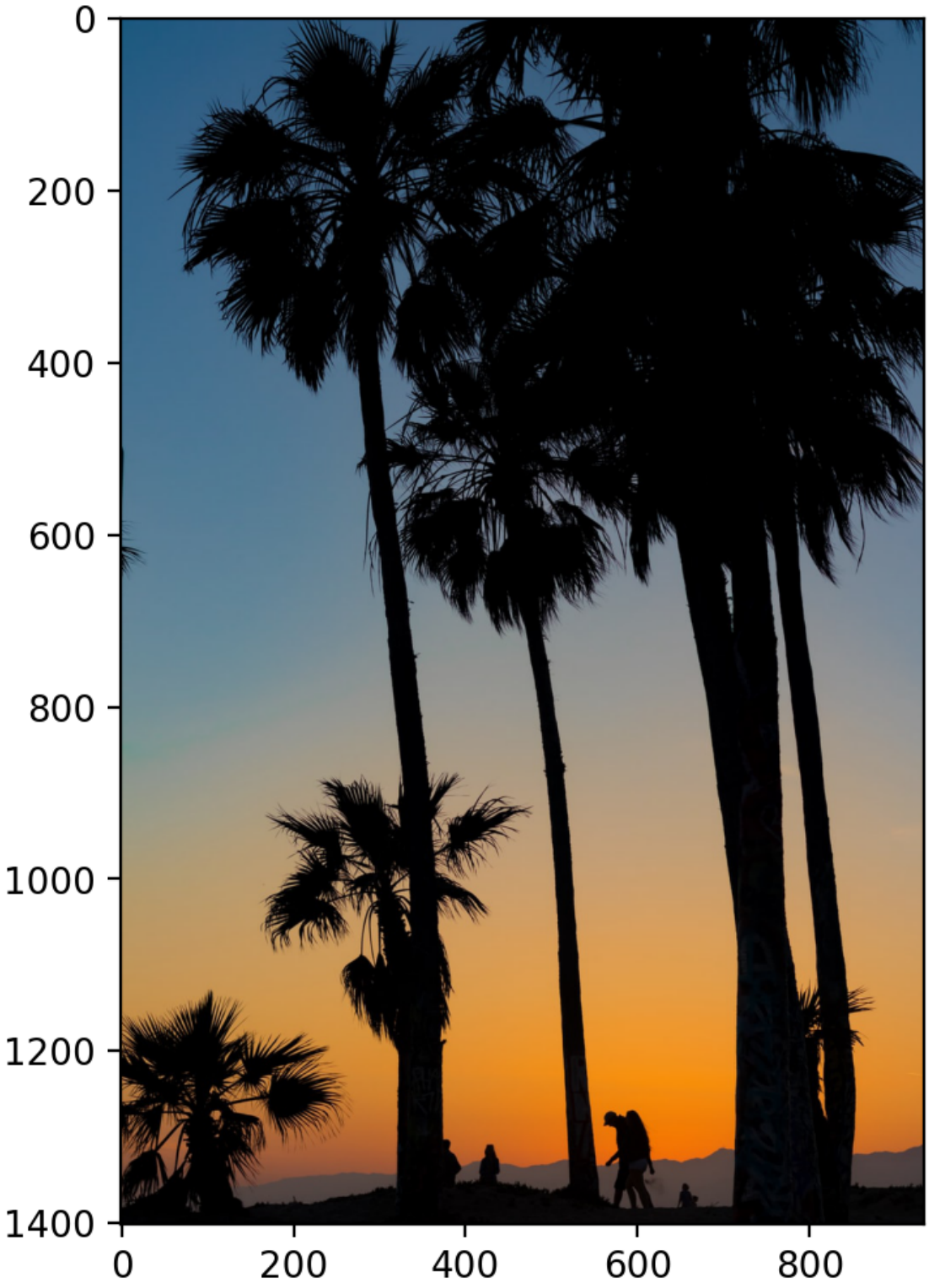
```
array([[[ 25,  89, 127],
        [ 25,  89, 127],
        [ 25,  89, 127],
        ...,
        [ 23,  63,  99],
        [ 51,  91, 127],
        [ 50,  90, 126]],

       [[ 25,  89, 127],
        [ 25,  89, 127],
        [ 25,  89, 127],
        ...,
        [ 31,  71, 107],
        [ 48,  88, 124],
        [ 47,  90, 125]],

       [[ 25,  89, 127],
        [ 25,  89, 127],
        [ 25,  89, 127],
        ...,
        [ 39,  79, 115],
        [ 42,  85, 120],
        [ 44,  88, 123]],

       ...,

       [[  4,   4,   6],
        [  4,   4,   6],
        [  4,   4,   6],
        ...,
        [  9,   9,  11],
        [  9,   9,  11],
        [  9,   9,  11]],

       [[  3,   3,   5],
        [  3,   3,   5],
        [  3,   3,   5],
        ...,
        [  8,   8,  10],
        [  8,   8,  10],
        [  8,   8,  10]],

       [[  4,   4,   6],
        [  4,   4,   6],
        [  4,   4,   6],
        ...,
        [  9,   9,  11],
        [ 10,  10,  12],
        [ 10,  10,  12]]], dtype=uint8)
```

In [102]:

```
plt.figure(figsize=(6,6),dpi=200)
plt.imshow(image_as_array)
```

Out[102]:

```
<matplotlib.image.AxesImage at 0x1e03bc72fd0>
```



Using Kmeans to Quantize Colors

Quantizing colors means we'll reduce the number of unique colors here to K unique colors. Let's try just 6 colors!

In [104]:

```
image_as_array.shape
# (h,w,3 color channels)
```

Out[104]:

```
(1401, 934, 3)
```

Convert from 3d to 2d

Kmeans is designed to train on 2D data (data rows and feature columns), so we can reshape the above strip by using (h,w,c) ---> (h * w,c)

In [117]:

```
len(image_as_array.shape)
```

Out[117]:

```
3
```

In [105]:

```
(h,w,c) = image_as_array.shape
```

In [106]:

```
h
```

Out[106]:

```
1401
```

In [107]:

```
w
```

Out[107]:

```
934
```

In [108]:

```
c
```

Out[108]:

```
3
```

In [112]:

```
image_as_array2d = image_as_array.reshape(h*w,c)
# (H,W,C) ----> 2D (H*W,C)
```

In [113]:

```
image_as_array2d
```

Out[113]:

```
array([[ 25,  89, 127],
       [ 25,  89, 127],
       [ 25,  89, 127],
       ...,
       [  9,   9,  11],
       [ 10,  10,  12],
       [ 10,  10,  12]], dtype=uint8)
```

In [114]:

```
image_as_array2d.shape
```

Out[114]:

```
(1308534, 3)
```

In [115]:

```
len(image_as_array2d.shape)
```

Out[115]:

```
2
```

In [118]:

```
from sklearn.cluster import KMeans
```

In [119]:

```
model = KMeans(n_clusters=6) # ^ average dub color
```

In [120]:

```
model
```

Out[120]:

```
KMeans(n_clusters=6)
```

In [129]:

```
labels = model.fit_predict(image_as_array2d) # KMean take 2d images only
```

```
C:\Users\Chromsy\AppData\Roaming\Python\Python39\site-packages\sklearn\clu
ster\_kmeans.py:870: FutureWarning: The default value of `n_init` will cha
nge from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to supp
ress the warning
  warnings.warn(
```

In [131]:

```
1401*934 #h*w
```

Out[131]:

```
1308534
```

In [122]:

```
labels # These numbers are meaning less
```

Out[122]:

```
array([3, 3, 3, ..., 0, 0, 0])
```

In [123]:

```
# THESE ARE THE 6 RGB COLOR CODES!
model.cluster_centers_
```

Out[123]:

```
array([[  2.75774918,   2.57625598,   3.70101918],
       [136.92096159, 143.80549772, 143.92085936],
       [219.05638325, 135.4139575 ,  46.95275156],
       [ 71.14229478, 109.2914198 , 137.70581831],
       [ 67.28313253,  61.57612148,  62.0460535 ],
       [191.64383719, 154.52989828, 109.44177973]])
```

In [124]:

```
rgb_codes = model.cluster_centers_.round(0).astype(int)
```

In [125]:

```
rgb_codes
```

Out[125]:

```
array([[  3,   3,   4],
       [137, 144, 144],
       [219, 135,  47],
       [ 71, 109, 138],
       [ 67,  62,  62],
       [192, 155, 109]])
```

In [126]:

```
quantized_image = np.reshape(rgb_codes[labels],(h,w,c))
```

In [127]:

```
quantized_image
```

Out[127]:

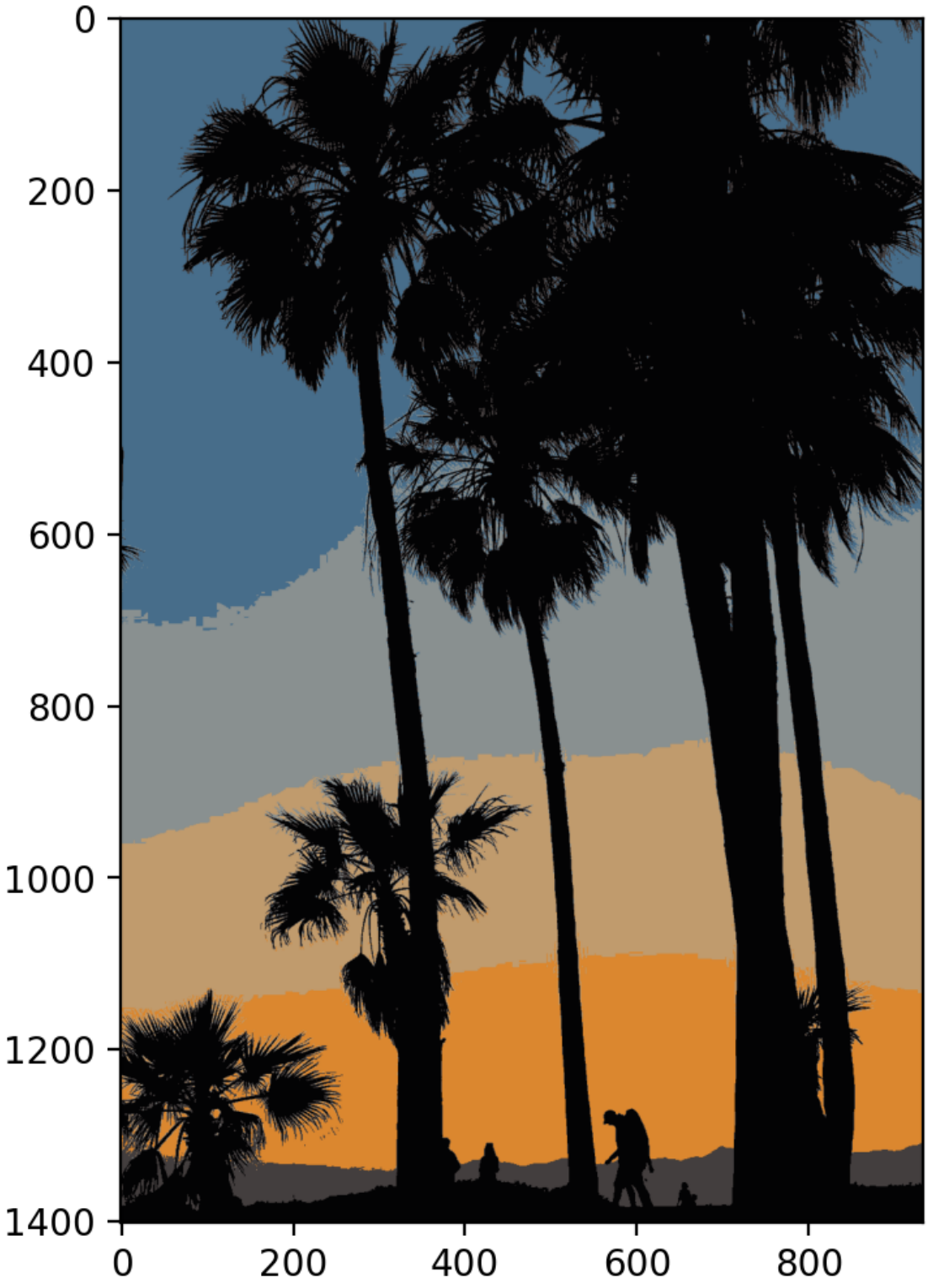
```
array([[[ 71, 109, 138],
        [ 71, 109, 138],
        [ 71, 109, 138],
        ...,
        [ 67,  62,  62],
        [ 71, 109, 138],
        [ 71, 109, 138]],

       [[ 71, 109, 138],
        [ 71, 109, 138],
        [ 71, 109, 138],
        ...,
        [ 67,  62,  62],
        [ 71, 109, 138],
        [ 71, 109, 138]],

       [[ 71, 109, 138],
        [ 71, 109, 138],
        [ 71, 109, 138],
        ...,
        [ 71, 109, 138],
        [ 71, 109, 138],
        [ 71, 109, 138]],

       ...,

       [[  3,   3,   4],
        [  3,   3,   4],
        [  3,   3,   4],
        ...,
        [  3,   3,   4],
        [  3,   3,   4],
        [  3,   3,   4]],

       [[  3,   3,   4],
        [  3,   3,   4],
        [  3,   3,   4],
        ...,
        [  3,   3,   4],
        [  3,   3,   4],
        [  3,   3,   4]],

       [[  3,   3,   4],
        [  3,   3,   4],
        [  3,   3,   4],
        ...,
        [  3,   3,   4],
        [  3,   3,   4],
        [  3,   3,   4]]])
```

In [128]:

```
plt.figure(figsize=(6,6),dpi=200)
plt.imshow(quantized_image)
```

Out[128]:

```
<matplotlib.image.AxesImage at 0x1e032acd280>
```



In [ ]: