作业二：频繁模式与关联规则挖掘

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姓名：白思萌学号：3120190975 学院：计算机学院

1 Wine Reviews 数据集

1.1 数据准备

数据集主页：https://www.kaggle.com/zynicide/wine-reviews

首先，导入数据分析与处理所需的数据模块。

[1]:
```
import pandas as pd
import itertools
import collections
import numbers
import typing
```

将数据集进行导入。

[2]:
```
wine = pd.read_csv('winemag-data-130k-v2.csv')
print('%d columns' % len(wine.columns))
print('%d rows' % len(wine.index))
```

```
14 columns
129971 rows
```

数据共有 14 列，129971 行。取前 5 行数据进行展示。

[3]:
```
wine.head(5)
```

[3]:
```
   Unnamed: 0   country                                        description  \
0           0     Italy  Aromas include tropical fruit, broom, brimston…
1           1  Portugal  This is ripe and fruity, a wine that is smooth…
2           2        US  Tart and snappy, the flavors of lime flesh and…
3           3        US  Pineapple rind, lemon pith and orange blossom …
4           4        US  Much like the regular bottling from 2012, this…

                          designation  points  price           province  \
0                        Vulkà Bianco      87    NaN  Sicily & Sardinia
1                            Avidagos      87   15.0              Douro
2                                 NaN      87   14.0             Oregon
```

```
3               Reserve Late Harvest      87    13.0           Michigan
4  Vintner's Reserve Wild Child Block      87    65.0             Oregon

             region_1           region_2         taster_name  \
0                Etna                NaN       Kerin O’ Keefe
1                 NaN                NaN          Roger Voss
2   Willamette Valley  Willamette Valley        Paul Gregutt
3 Lake Michigan Shore                NaN  Alexander Peartree
4   Willamette Valley  Willamette Valley        Paul Gregutt

  taster_twitter_handle                                              title  \
0          @kerinokeefe                  Nicosia 2013 Vulkà Bianco  (Etna)
1             @vossroger      Quinta dos Avidagos 2011 Avidagos Red (Douro)
2            @paulgwine       Rainstorm 2013 Pinot Gris (Willamette Valley)
3                   NaN  St. Julian 2013 Reserve Late Harvest Riesling …
4            @paulgwine   Sweet Cheeks 2012 Vintner's Reserve Wild Child…

         variety               winery
0    White Blend              Nicosia
1 Portuguese Red  Quinta dos Avidagos
2     Pinot Gris            Rainstorm
3       Riesling           St. Julian
4     Pinot Noir         Sweet Cheeks
```

1.2 对数据集进行处理，转换成适合进行关联规则挖掘的形式

经对数据的分析后，此次将对葡萄酒的 country，designation，province，variety，winery 属性进行关系分析。因此将这五列数据进行抽取，缺失值用 nan 代替。

[4]:
```
columns = [
    'country',
    'designation',
    'province',
    'variety',
    'winery'
]
wine = wine[columns].fillna('nan')

transactions = wine.values.tolist()

print('%d transactions.' % len(transactions), end='\n\n')
for idx, t in enumerate(transactions[:5]):
    print('%d:' % idx, t, end='\n\n')
```

```
129971 transactions.

0: ['Italy', 'Vulkà Bianco', 'Sicily & Sardinia', 'White Blend', 'Nicosia']
```

```
1: ['Portugal', 'Avidagos', 'Douro', 'Portuguese Red', 'Quinta dos Avidagos']

2: ['US', 'nan', 'Oregon', 'Pinot Gris', 'Rainstorm']

3: ['US', 'Reserve Late Harvest', 'Michigan', 'Riesling', 'St. Julian']

4: ['US', "Vintner's Reserve Wild Child Block", 'Oregon', 'Pinot Noir', 'Sweet
Cheeks']
```

以上结果表明对 5 列属性抽取成功，共包含 129971 行数据。前 5 行数据如上所示。

1.3 找出频繁模式

1.3.1 算法构造

采用 Apriori 算法找出频繁项集。首先构造 find_itemsets() 函数用于找出频繁项集。

[5]:
```python
def join_step(itemsets: typing.List[tuple]):
    i = 0
    while i < len(itemsets):
        skip = 1
        *itemset_first, itemset_last = itemsets[i]
        tail_items = [itemset_last]
        tail_items_append = tail_items.append  # Micro-optimization
        for j in range(i + 1, len(itemsets)):
            *itemset_n_first, itemset_n_last = itemsets[j]
            if itemset_first == itemset_n_first:
                tail_items_append(itemset_n_last)
                skip += 1
            else:
                break
        itemset_first = tuple(itemset_first)
        for a, b in sorted(itertools.combinations(tail_items, 2)):
            yield itemset_first + (a,) + (b,)
        i += skip


def prune_step(
    itemsets: typing.List[tuple],
    possible_itemsets: typing.List[tuple]
):
    itemsets = set(itemsets)
    for possible_itemset in possible_itemsets:
        for i in range(len(possible_itemset) - 2):
            removed = possible_itemset[:i] + possible_itemset[i + 1 :]
            if removed not in itemsets:
                break
        else:
```

```python
            yield possible_itemset


def apriori_gen(itemsets: typing.List[tuple]):
    possible_extensions = join_step(itemsets)
    yield from prune_step(itemsets, possible_extensions)


def find_itemsets(
    transactions: typing.List[tuple],
    min_support: float,
    max_length: int = 8,
    verbosity: int = 0,
):
    transaction_sets = [set(t) for t in transactions if len(t) > 0]
    transactions = transaction_sets
    use_transaction = collections.defaultdict(lambda: True)

    if verbosity > 0:
        print("开始寻找频繁项集")
        print(" 项集长度为 1: ")

    counts = collections.defaultdict(int)
    num_transactions = 0
    for transaction in transactions:
        num_transactions += 1  # Increment counter for transactions
        for item in transaction:
            counts[item] += 1  # Increment counter for single-item itemsets

    large_itemsets = [
        (i, c)
        for (i, c) in counts.items()
        if (c / num_transactions) >= min_support
    ]

    if verbosity > 0:
        num_cand, num_itemsets = len(counts.items()), len(large_itemsets)
        print(" 找到 {} 个长度为 1 的项集".format(num_cand))
        print("  找到 {} 个长度为 1 的频繁项集".format(num_itemsets))

    # If large itemsets were found, convert to dictionary
    if large_itemsets:
        large_itemsets = {1: {(i,): c for (i, c) in sorted(large_itemsets)}}
    else:
        return dict(), num_transactions

    issubset = set.issubset  # Micro-optimization
```

```python
    k = 2
    while large_itemsets[k - 1] and (max_length != 1):
        if verbosity > 0:
            print("项集长度为 {} : ".format(k))
        itemsets_list = list(large_itemsets[k - 1].keys())
        C_k = list(apriori_gen(itemsets_list))
        C_k_sets = [set(itemset) for itemset in C_k]

        if verbosity > 0:
            print("  找到 {} 个长度为 {} 的项集".format(len(C_k), k))
        if not C_k:
            break

        # Prepare counts of candidate itemsets (from the pruen step)
        candidate_itemset_counts = collections.defaultdict(int)
        if verbosity > 1:
            print("    继续寻找")
        for row, transaction in enumerate(transactions):
            if not use_transaction[row]:
                continue
            found_any = False
            for candidate, candidate_set in zip(C_k, C_k_sets):
                if issubset(candidate_set, transaction):
                    candidate_itemset_counts[candidate] += 1
                    found_any = True
            if not found_any:
                use_transaction[row] = False

        C_k = [
            (i, c)
            for (i, c) in candidate_itemset_counts.items()
            if (c / num_transactions) >= min_support
        ]
        if not C_k:
            break

        large_itemsets[k] = {i: c for (i, c) in sorted(C_k)}

        if verbosity > 0:
            num_found = len(large_itemsets[k])
            pp = "  找到 {} 个长度为 {} 的频繁项集".format(num_found, k)
            print(pp)
        k += 1
        if k > max_length:
            break

    if verbosity > 0:
```

```
        print("寻找结束")
    return large_itemsets, num_transactions
```

1.3.2 算法实现

找出支持度大于等于 0.05 的频繁项集。

[6]:
```
itemsets, num_trans = find_itemsets(
    transactions=transactions,
    min_support=0.05,
    verbosity=1,
)
```

```
开始寻找频繁项集
 项集长度为 1:
 找到 54849 个长度为 1 的项集
  找到 12 个长度为 1 的频繁项集
项集长度为 2 :
  找到 66 个长度为 2 的项集
  找到 9 个长度为 2 的频繁项集
项集长度为 3 :
  找到 2 个长度为 3 的项集
  找到 2 个长度为 3 的频繁项集
项集长度为 4 :
  找到 0 个长度为 4 的项集
寻找结束
```

输出所有找到的频繁项集。

[7]:
```
for k, itemset in itemsets.items():
    print('长度为 %s 的频繁项集:' % k)
    for items in itemset:
        print(items)
    print()
```

```
长度为 1 的频繁项集:
('Bordeaux-style Red Blend',)
('Cabernet Sauvignon',)
('California',)
('Chardonnay',)
('France',)
('Italy',)
('Pinot Noir',)
('Red Blend',)
('Spain',)
('US',)
('Washington',)
('nan',)
```

```
长度为 2 的频繁项集:
('Cabernet Sauvignon', 'US')
('California', 'Pinot Noir')
('California', 'US')
('California', 'nan')
('Chardonnay', 'US')
('France', 'nan')
('Pinot Noir', 'US')
('US', 'Washington')
('US', 'nan')

长度为 3 的频繁项集:
('California', 'Pinot Noir', 'US')
('California', 'US', 'nan')
```

1.4 导出关联规则，计算其支持度和置信度

1.4.1 算法构造

首先，定义关联规则类 Rule。

[8]:
```python
class Rule(object):
    _decimals = 3

    def __init__(
        self,
        lhs: tuple,
        rhs: tuple,
        count_full: int = 0,
        count_lhs: int = 0,
        count_rhs: int = 0,
        num_transactions: int = 0,
    ):
        self.lhs = lhs  # antecedent
        self.rhs = rhs  # consequent
        self.count_full = count_full
        self.count_lhs = count_lhs
        self.count_rhs = count_rhs
        self.num_transactions = num_transactions

    @property
    def confidence(self):
        try:
            return self.count_full / self.count_lhs
        except ZeroDivisionError:
            return None
        except AttributeError:
```

```python
            return None

    @property
    def support(self):
        try:
            return self.count_full / self.num_transactions
        except ZeroDivisionError:
            return None
        except AttributeError:
            return None

    @staticmethod
    def _pf(s):
        return "{" + ", ".join(str(k) for k in s) + "}"

    def __str__(self):
        return "{} => {}".format(self._pf(self.lhs), self._pf(self.rhs))

    def __eq__(self, other):
        return (set(self.lhs) == set(other.lhs)) and (
            set(self.rhs) == set(other.rhs)
        )

    def __hash__(self):
        return hash(frozenset(self.lhs + self.rhs))

    def __len__(self):
        return len(self.lhs + self.rhs)
```

然后，构造函数 rules_apriori() 来实现导出关联规则。

[9]:
```python
def rules_apriori(
    itemsets: typing.Dict[int, typing.Dict[tuple, int]],
    min_confidence: float,
    num_transactions: int,
    verbosity: int = 0,
):
    def count(itemset):
        return itemsets[len(itemset)][itemset]

    if verbosity > 0:
        print("开始导出关联规则")

    for size in itemsets.keys():
        if size < 2:
            continue
        if verbosity > 0:
```

```
            print(" 开始从频繁项集长度为 {} 中导出关联规则".format(size))

        for itemset in itemsets[size].keys():
            for removed in itertools.combinations(itemset, 1):
                lhs = set(itemset).difference(set(removed))
                lhs = tuple(sorted(list(lhs)))
                conf = count(itemset) / count(lhs)
                if conf >= min_confidence:
                    yield Rule(
                        lhs,
                        removed,
                        count(itemset),
                        count(lhs),
                        count(removed),
                        num_transactions,
                    )

            H_1 = list(itertools.combinations(itemset, 1))
            yield from _ap_genrules(
                itemset, H_1, itemsets, min_confidence, num_transactions
            )

    if verbosity > 0:
        print("关联规则导出完成")


def _ap_genrules(
    itemset: tuple,
    H_m: typing.List[tuple],
    itemsets: typing.Dict[int, typing.Dict[tuple, int]],
    min_conf: float,
    num_transactions: int,
):

    def count(itemset):
        return itemsets[len(itemset)][itemset]

    if len(itemset) <= (len(H_m[0]) + 1):
        return

    H_m = list(apriori_gen(H_m))
    H_m_copy = H_m.copy()

    for h_m in H_m:
        lhs = tuple(sorted(list(set(itemset).difference(set(h_m)))))
        if (count(itemset) / count(lhs)) >= min_conf:
            yield Rule(
```

```
                lhs,
                h_m,
                count(itemset),
                count(lhs),
                count(h_m),
                num_transactions,
            )
        else:
            H_m_copy.remove(h_m)
    if H_m_copy:
        yield from _ap_genrules(
            itemset, H_m_copy, itemsets, min_conf, num_transactions
        )
```

1.4.2 算法实现

实施函数 rules_apriori() 对关联规则进行导出，设置最小支持度为 0.1。

[10]:

```
rules = rules_apriori(
    itemsets=itemsets,
    min_confidence=0.1,
    num_transactions=num_trans,
    verbosity=1,
)
rules = list(rules)
```

```
开始导出关联规则
 开始从频繁项集长度为 2 中导出关联规则
 开始从频繁项集长度为 3 中导出关联规则
关联规则导出完成
```

对导出的关联规则进行展示，并计算支持度和置信度。

[11]:

```
rules_t = []
for rule in rules:
    valid = True
    for val in rule.lhs + rule.rhs:
        if 'nan' in val:
            valid = False
            break
    if valid:
        rules_t.append(rule)
rules = rules_t

rules_df = pd.DataFrame({
    'Rules': rules,
    'Left': list(map(lambda x: x.lhs, rules)),
    'Right': list(map(lambda x: x.rhs, rules)),
```

```python
    'Support': list(map(lambda x: x.support, rules)),
    'Confidence': list(map(lambda x: x.confidence, rules)),
})
rules_df
```

[11]:

```
                                Rules                     Left  \
0        {US} => {Cabernet Sauvignon}                    (US,)
1        {Cabernet Sauvignon} => {US}    (Cabernet Sauvignon,)
2        {Pinot Noir} => {California}            (Pinot Noir,)
3        {California} => {Pinot Noir}            (California,)
4                {US} => {California}                    (US,)
5                {California} => {US}            (California,)
6                {US} => {Chardonnay}                    (US,)
7                {Chardonnay} => {US}            (Chardonnay,)
8                {US} => {Pinot Noir}                    (US,)
9                {Pinot Noir} => {US}            (Pinot Noir,)
10               {Washington} => {US}            (Washington,)
11               {US} => {Washington}                    (US,)
12   {Pinot Noir, US} => {California}         (Pinot Noir, US)
13   {California, US} => {Pinot Noir}         (California, US)
14   {California, Pinot Noir} => {US}  (California, Pinot Noir)
15   {US} => {California, Pinot Noir}                    (US,)
16   {Pinot Noir} => {California, US}            (Pinot Noir,)
17   {California} => {Pinot Noir, US}            (California,)

                        Right   Support  Confidence
0       (Cabernet Sauvignon,)  0.056289    0.134229
1                       (US,)  0.056289    0.771730
2               (California,)  0.053081    0.518644
3               (Pinot Noir,)  0.053081    0.190333
4               (California,)  0.278885    0.665034
5                       (US,)  0.278885    1.000000
6               (Chardonnay,)  0.052350    0.124835
7                       (US,)  0.052350    0.578768
8               (Pinot Noir,)  0.076240    0.181803
9                       (US,)  0.076240    0.744926
10                      (US,)  0.066469    1.000000
11              (Washington,)  0.066469    0.158502
12              (California,)  0.053081    0.696236
13              (Pinot Noir,)  0.053081    0.190333
14                      (US,)  0.053081    1.000000
15   (California, Pinot Noir)  0.053081    0.126578
16             (California, US)  0.053081    0.518644
17             (Pinot Noir, US)  0.053081    0.190333
```

1.5 对规则进行评价

1.5.1 Lift 指标

对上述关联规则使用 Lift 指标进行评价。

[12]:
```python
def lift(rule):
    observed_support = rule.count_full / rule.num_transactions
    prod_counts = rule.count_lhs * rule.count_rhs
    expected_support = (prod_counts) / rule.num_transactions ** 2
    return observed_support / expected_support
```

[13]:
```python
rules_df['Lift'] = list(map(lambda x: lift(x), rules))
rules_df
```

[13]:
```
                                  Rules                        Left  \
0         {US} => {Cabernet Sauvignon}                       (US,)
1         {Cabernet Sauvignon} => {US}       (Cabernet Sauvignon,)
2         {Pinot Noir} => {California}               (Pinot Noir,)
3         {California} => {Pinot Noir}               (California,)
4                 {US} => {California}                       (US,)
5                 {California} => {US}               (California,)
6                 {US} => {Chardonnay}                       (US,)
7                 {Chardonnay} => {US}               (Chardonnay,)
8                 {US} => {Pinot Noir}                       (US,)
9                 {Pinot Noir} => {US}               (Pinot Noir,)
10                {Washington} => {US}               (Washington,)
11                {US} => {Washington}                       (US,)
12    {Pinot Noir, US} => {California}            (Pinot Noir, US)
13    {California, US} => {Pinot Noir}            (California, US)
14    {California, Pinot Noir} => {US}    (California, Pinot Noir)
15    {US} => {California, Pinot Noir}                       (US,)
16    {Pinot Noir} => {California, US}               (Pinot Noir,)
17    {California} => {Pinot Noir, US}               (California,)

                         Right   Support  Confidence      Lift
0        (Cabernet Sauvignon,)  0.056289    0.134229  1.840278
1                        (US,)  0.056289    0.771730  1.840278
2                (California,)  0.053081    0.518644  1.859703
3                (Pinot Noir,)  0.053081    0.190333  1.859703
4                (California,)  0.278885    0.665034  2.384614
5                        (US,)  0.278885    1.000000  2.384614
6                (Chardonnay,)  0.052350    0.124835  1.380139
7                        (US,)  0.052350    0.578768  1.380139
8                (Pinot Noir,)  0.076240    0.181803  1.776360
9                        (US,)  0.076240    0.744926  1.776360
10                       (US,)  0.066469    1.000000  2.384614
11               (Washington,)  0.066469    0.158502  2.384614
```

```
12             (California,)  0.053081    0.696236  2.496495
13             (Pinot Noir,)  0.053081    0.190333  1.859703
14                     (US,)  0.053081    1.000000  2.384614
15  (California, Pinot Noir)  0.053081    0.126578  2.384614
16          (California, US)  0.053081    0.518644  1.859703
17          (Pinot Noir, US)  0.053081    0.190333  2.496495
```

1.5.2 Conviction 指标

对上述关联规则使用 Conviction 指标进行评价。

[16]:
```python
def conviction(self):
    eps = 10e-10  # Avoid zero division
    prob_not_rhs = 1 - self.count_rhs / self.num_transactions
    prob_not_rhs_given_lhs = 1 - self.confidence
    return prob_not_rhs / (prob_not_rhs_given_lhs + eps)
```

[17]:
```python
rules_df['Conviction'] = list(map(lambda x: conviction(x), rules))
rules_df
```

[17]:
```
                                   Rules                      Left  \
0       {US} => {Cabernet Sauvignon}                      (US,)
1       {Cabernet Sauvignon} => {US}     (Cabernet Sauvignon,)
2       {Pinot Noir} => {California}             (Pinot Noir,)
3       {California} => {Pinot Noir}             (California,)
4               {US} => {California}                     (US,)
5               {California} => {US}             (California,)
6               {US} => {Chardonnay}                     (US,)
7               {Chardonnay} => {US}             (Chardonnay,)
8               {US} => {Pinot Noir}                     (US,)
9               {Pinot Noir} => {US}             (Pinot Noir,)
10              {Washington} => {US}             (Washington,)
11              {US} => {Washington}                     (US,)
12  {Pinot Noir, US} => {California}          (Pinot Noir, US)
13  {California, US} => {Pinot Noir}          (California, US)
14  {California, Pinot Noir} => {US}  (California, Pinot Noir)
15  {US} => {California, Pinot Noir}                     (US,)
16  {Pinot Noir} => {California, US}             (Pinot Noir,)
17  {California} => {Pinot Noir, US}             (California,)

                    Right   Support  Confidence      Lift    Conviction
0     (Cabernet Sauvignon,)  0.056289    0.134229  1.840278  1.070792e+00
1                     (US,)  0.056289    0.771730  1.840278  2.543675e+00
2             (California,)  0.053081    0.518644  1.859703  1.498090e+00
3             (Pinot Noir,)  0.053081    0.190333  1.859703  1.108671e+00
4             (California,)  0.278885    0.665034  2.384614  2.152798e+00
5                     (US,)  0.278885    1.000000  2.384614  5.806449e+08
```

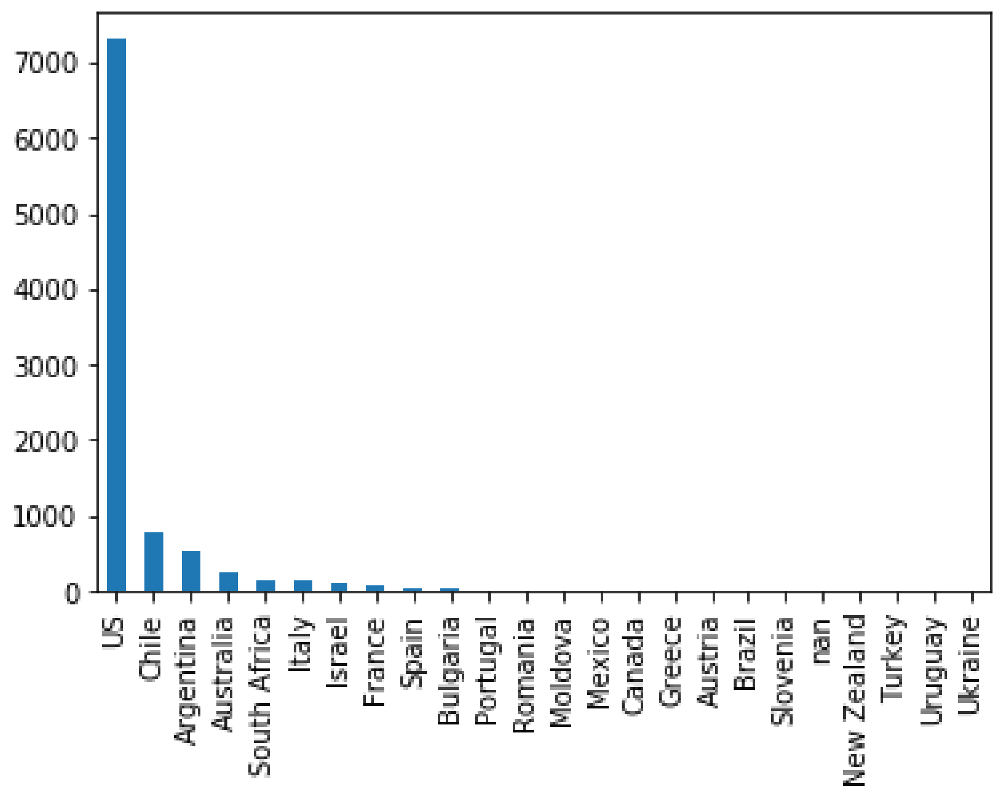
6	(Chardonnay,)	0.052350	0.124835	1.380139	1.039289e+00
7	(US,)	0.052350	0.578768	1.380139	1.378445e+00
8	(Pinot Noir,)	0.076240	0.181803	1.776360	1.097113e+00
9	(US,)	0.076240	0.744926	1.776360	2.276374e+00
10	(US,)	0.066469	1.000000	2.384614	5.806449e+08
11	(Washington,)	0.066469	0.158502	2.384614	1.109369e+00
12	(California,)	0.053081	0.696236	2.496495	2.373929e+00
13	(Pinot Noir,)	0.053081	0.190333	1.859703	1.108671e+00
14	(US,)	0.053081	1.000000	2.384614	5.806449e+08
15	(California, Pinot Noir)	0.053081	0.126578	2.384614	1.084148e+00
16	(California, US)	0.053081	0.518644	1.859703	1.498090e+00
17	(Pinot Noir, US)	0.053081	0.190333	2.496495	1.140913e+00

1.6 对挖掘结果进行可视化展示

以 {Cabernet Sauvignon} => {US} 此项关联规则为例，直方图展示品种为 Cabernet Sauvignon 的葡萄酒的产地信息，从而判断是否大部分产自于美国。

[22]:
```
wine[wine['variety'] == 'Cabernet Sauvignon']['country'].value_counts().
↪plot(kind='bar')
```

[22]: <matplotlib.axes._subplots.AxesSubplot at 0x16003f48d08>



从直方图的统计结果看，US 的数值最多。因此可认为品种为 Cabernet Sauvignon 的葡萄酒大部分产自于美国，从而认为此关联规则有效。