Practice Exam

```
Scoring:
============
 0-11: fail (1),
12-14: pass (2),
15-17: satisfactory (3),
18-20: good (4),
21-24: excellent (5).
```

The file forestfires.txt contains data about forest fires in Portugal. Write a program that estimates the value of the *area* feature from the other features! Apply 5-fold cross-validation! The error metric should be the root mean squared error (RMSE).

Subproblems:

(a) Perform initial data analysis! Prepare the input matrix X and the target vector y! [4 points]

(b) Create a t-SNE based visualization of the input features! [4 points]

(c) Introduce at least one new feature that is a engineered from the original ones. [4 points]

(d) Create a non-tree based estimator and optimize its hyper-parameters! [6 points]

(e) Create a tree based estimator and optimize its hyper-parameters! [6 points]

(a) Perform initial data analysis! Prepare the input matrix X and the target vector y! [4 points]

In [5]:

```
# Read data from CSV file.
import pandas as pd
fname = 'forestfires.txt'
df = pd.read_csv(fname)
```

In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 517 entries, 0 to 516
Data columns (total 13 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   X       517 non-null    int64  
 1   Y       517 non-null    int64  
 2   month   517 non-null    object 
 3   day     517 non-null    object 
 4   FFMC    517 non-null    float64
 5   DMC     517 non-null    float64
 6   DC      517 non-null    float64
 7   ISI     517 non-null    float64
 8   temp    517 non-null    float64
 9   RH      517 non-null    int64  
 10  wind    517 non-null    float64
 11  rain    517 non-null    float64
 12  area    517 non-null    float64
dtypes: float64(8), int64(3), object(2)
memory usage: 52.6+ KB
```

- there are no null values
- month and day are strings

In [7]:
```
# columns stats
df.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
X	517.0	4.669246	2.313778	1.0	3.0	4.00	7.00	9.00
Y	517.0	4.299807	1.229900	2.0	4.0	4.00	5.00	9.00
FFMC	517.0	90.644681	5.520111	18.7	90.2	91.60	92.90	96.20
DMC	517.0	110.872340	64.046482	1.1	68.6	108.30	142.40	291.30
DC	517.0	547.940039	248.066192	7.9	437.7	664.20	713.90	860.60
ISI	517.0	9.021663	4.559477	0.0	6.5	8.40	10.80	56.10
temp	517.0	18.889168	5.806625	2.2	15.5	19.30	22.80	33.30
RH	517.0	44.288201	16.317469	15.0	33.0	42.00	53.00	100.00
wind	517.0	4.017602	1.791653	0.4	2.7	4.00	4.90	9.40
rain	517.0	0.021663	0.295959	0.0	0.0	0.00	0.00	6.40
area	517.0	12.847292	63.655818	0.0	0.0	0.52	6.57	1090.84

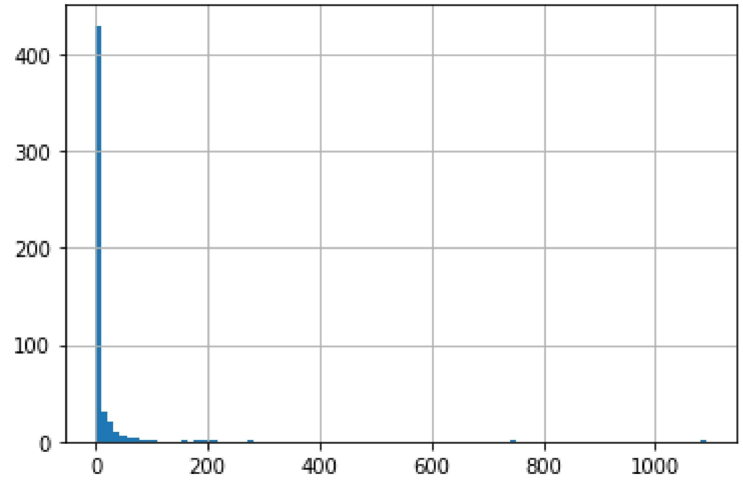
- standard deviations are quite different
- max(area) is much bigger than the 75-percentile.

In [15]:

```
# histogram of area
df['area'].hist(bins=100)
```

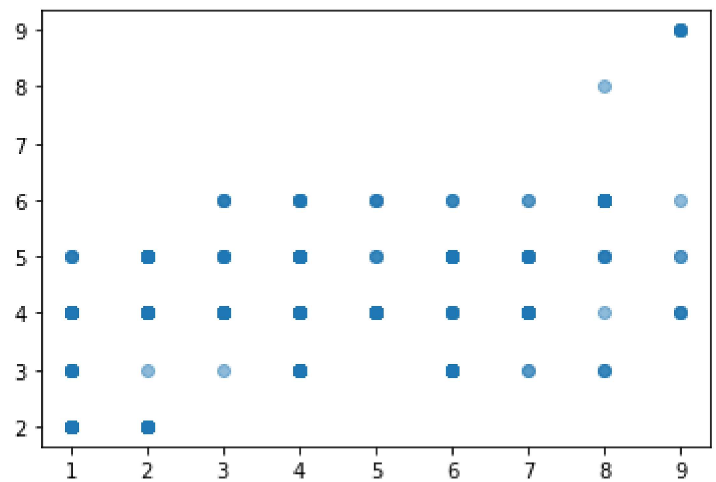
Out[15]:

```
<AxesSubplot: >
```



In [19]:
```python
# scatter plot of (X, Y)
import matplotlib.pyplot as plt
plt.scatter(df['X'], df['Y'], alpha=0.5)
```

Out[19]:
```
<matplotlib.collections.PathCollection at 0x7f3098439490>
```



In [21]:
```python
# possible values of month
df['month'].unique(), df['month'].nunique()
```

Out[21]:
```
(array(['mar', 'oct', 'aug', 'sep', 'apr', 'jun', 'jul', 'feb', 'jan',
        'dec', 'may', 'nov'], dtype=object),
 12)
```

In [22]:
```
# possible values of day
df['day'].unique(), df['day'].nunique()
```

Out[22]:
```
(array(['fri', 'tue', 'sat', 'sun', 'mon', 'wed', 'thu'], dtype=object), 7)
```

In [28]:
```
columns = ['X', 'Y', 'FFMC', 'DMC', 'DC', 'ISI', 'temp', 'RH', 'wind', 'rain']
X = df[columns].values # input matrix
y = df['area'].values  # target vector
```

In [32]:
```
X.shape, y.shape, X.mean(), y.mean()
```

Out[32]:
```
((517, 10), (517,), 83.46644100580271, 12.847292069632493)
```

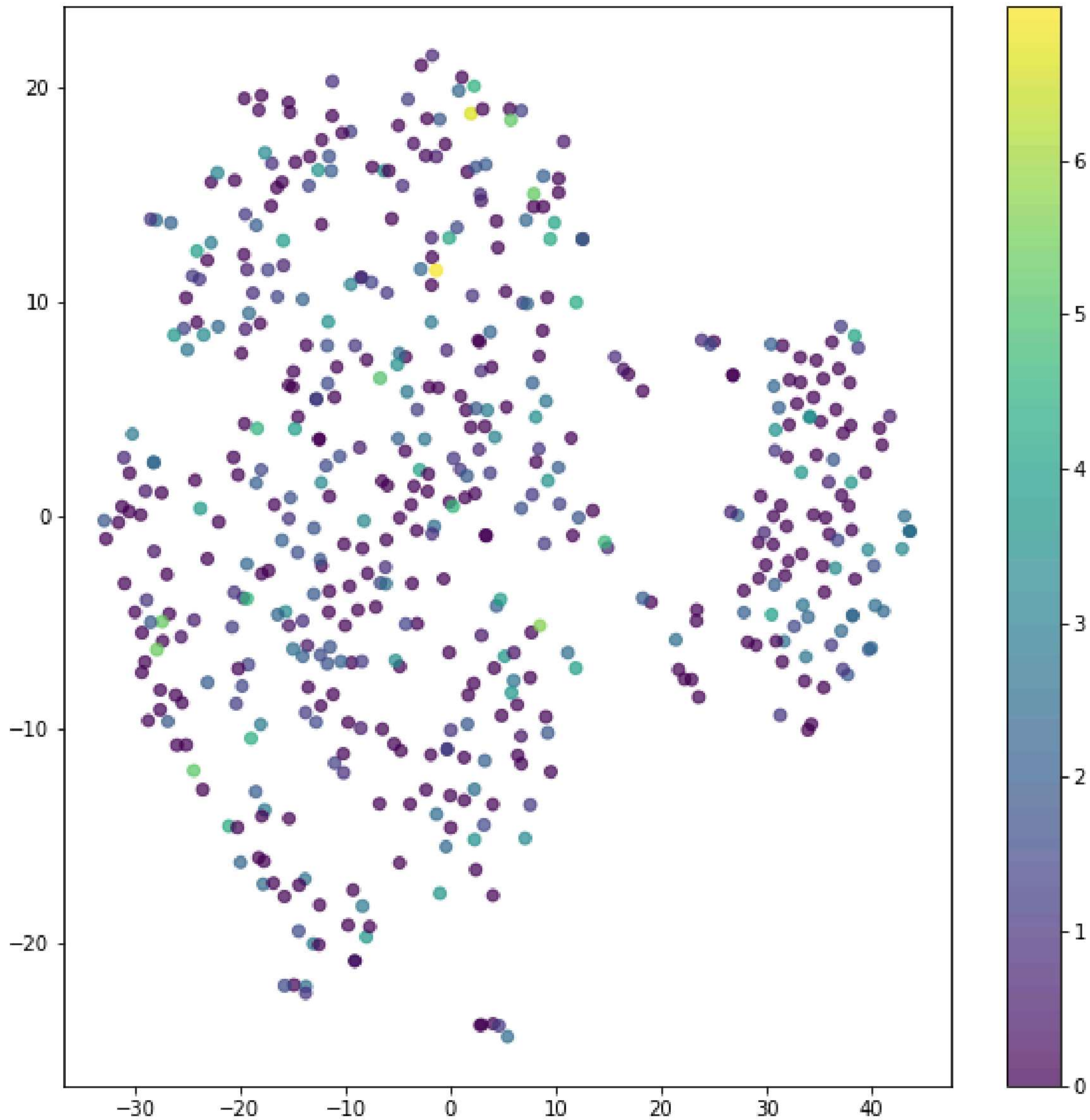
In [35]:
```
from sklearn.preprocessing import StandardScaler
X2 = StandardScaler().fit_transform(X) # standardize input matrix
```

(b) Create a t-SNE based visualization of the input features! [4 points]

In [39]:
```
from sklearn.manifold import TSNE
Z = TSNE(random_state=42).fit_transform(X2)
```

In [51]:
```
import numpy as np
plt.figure(figsize=(10, 10))
plt.scatter(Z[:, 0], Z[:, 1], c=np.log(y + 1), alpha=0.7)
plt.colorbar()
```

Out[51]:
```
<matplotlib.colorbar.Colorbar at 0x7f3089c08580>
```



(c) Introduce at least one new feature that is a engineered from the original ones. [4 points]

In [58]:
```
# convert month name to month index
month_idxs = {
    'jan': 1, 'feb': 2, 'mar': 3, 'apr': 4, 'may': 5, 'jun': 6,
    'jul': 7, 'aug': 8, 'sep': 9, 'oct': 10, 'nov': 11, 'dec': 12,
```

```
}
df['month_idx'] = [month_idxs[m] for m in df['month']]
```

In [63]:
```
# convert weekday name to weekday index
day_idxs = {
    'mon': 1, 'tue': 2, 'wed': 3, 'thu': 4, 'fri': 5, 'sat': 6,'sun': 7
}
df['day_idx'] = [day_idxs[d] for d in df['day']]
```

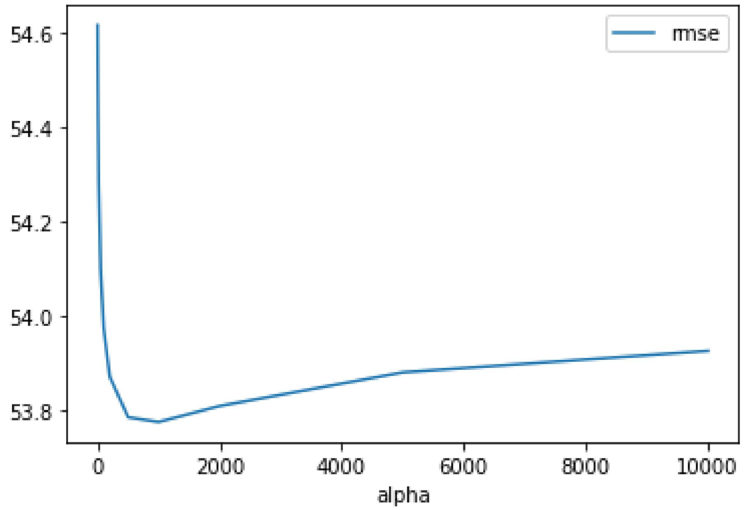
(d) Create a non-tree based estimator and optimize its hyper-parameters! [6 points]

In [78]:
```
# Ridge regression with default parameters.
from sklearn.linear_model import Ridge
from sklearn.model_selection import KFold
from sklearn.metrics import mean_squared_error

def evaluate(re, X, y):
    cv = KFold(shuffle=True, random_state=42)
    scores = []
    for tr, te in cv.split(X):
        re.fit(X[tr], y[tr])
        yhat = re.predict(X)
        rmse = mean_squared_error(y[te], yhat[te])**0.5
        scores.append(rmse)
    return np.mean(scores)

X3 = StandardScaler().fit_transform(df[columns + ['month_idx', 'day_idx']].values)
evaluate(Ridge(), X3, y)
```

Out[78]:
```
54.58729606435613
```

In [88]:
```
# Hyperparameter optimization.
alphas = [0.01, 0.02, 0.05, 0.1, 0.2, 0.5, 1, 2, 5, 10, 20, 50, 100, 200, 500, 1000, 2000, 5000, 10000]
res = []
for alpha in alphas:
    res.append({
        'alpha': alpha,
        'rmse': evaluate(Ridge(alpha=alpha), X3, y)
    })
df_res = pd.DataFrame(res).set_index('alpha')
df_res.plot()
```

Out[88]: <AxesSubplot: xlabel='alpha'>



In [91]:
```
df_res['rmse'].idxmin(), df_res['rmse'].min()
```

Out[91]: (1000.0, 53.77504142548006)

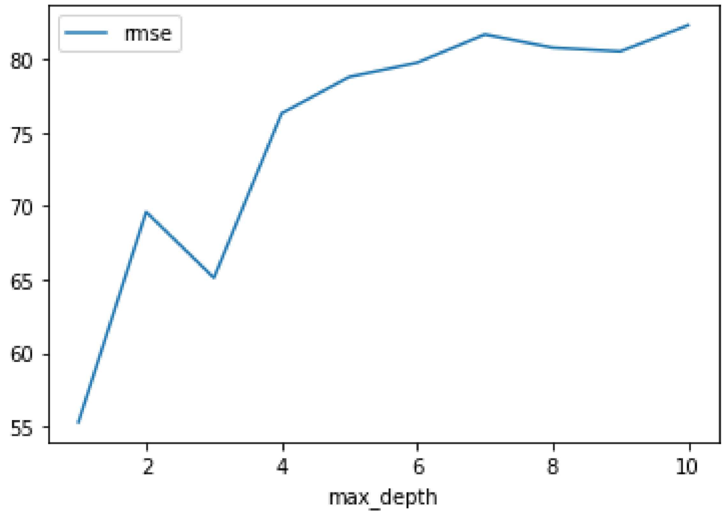
(e) Create a tree based estimator and optimize its hyper-parameters! [6 points]

In [95]:
```
from sklearn.ensemble import GradientBoostingRegressor

evaluate(GradientBoostingRegressor(random_state=42), X3, y)
```

Out[95]: 65.06556168485034

In [96]:
```
# Hyperparameter optimization.
res = []
for max_depth in range(1, 11):
    print(max_depth, end=' ')
    res.append({
        'max_depth': max_depth,
        'rmse': evaluate(GradientBoostingRegressor(max_depth=max_depth), X3, y)
    })
df_res = pd.DataFrame(res).set_index('max_depth')
df_res.plot()
```

Out[96]: <AxesSubplot: xlabel='max_depth'>



In [97]:
```
df_res['rmse'].idxmin(), df_res['rmse'].min()
```

Out[97]: (1, 55.321957821450226)