In [2]:

```
import numpy as np
from scipy import stats, optimize
import matplotlib.pyplot as plt
%matplotlib inline
```

In [3]:

```
noise = stats.norm(scale=np.sqrt(0.2)).rvs(500)
```

In [4]:

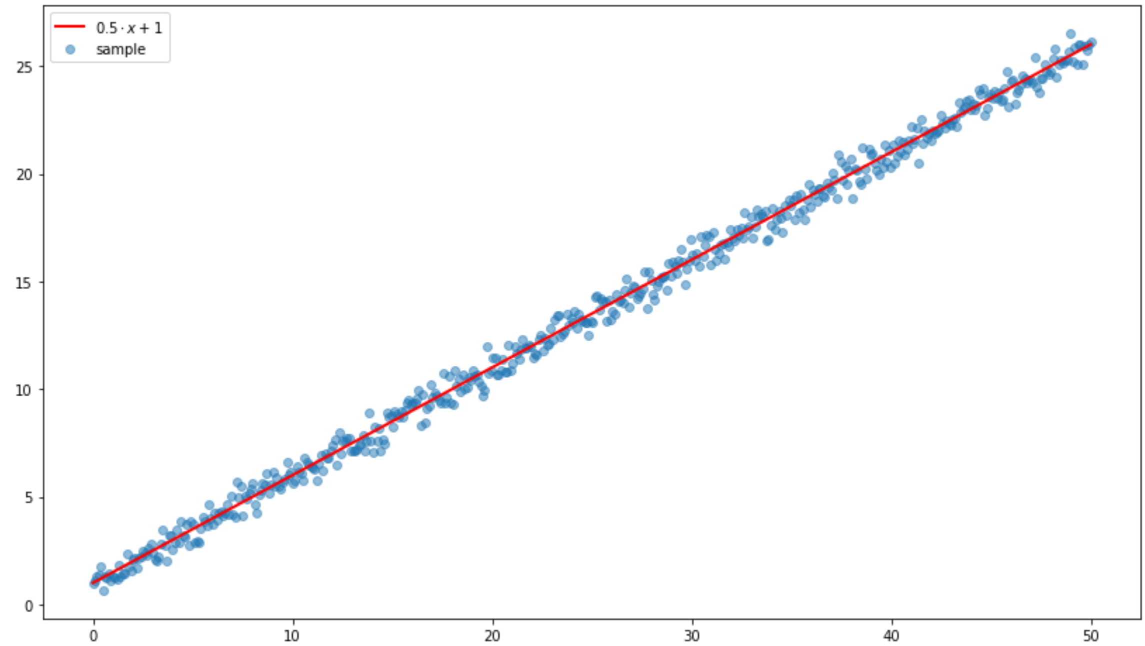
```
xs = np.linspace(0, 50, 500)
```

In [5]:

```
sample = 0.5 * xs + 1 + noise
```

In [6]:

```
plt.figure(figsize=(14,8))
plt.scatter(xs, sample, alpha=0.5, label='sample')
plt.plot(xs, 0.5 * xs + 1, c='red', linewidth=2, label='$0.5 \cdot x + 1$')
plt.legend()
plt.show()
```



In [7]:

```
from sklearn import metrics
```

In [8]:

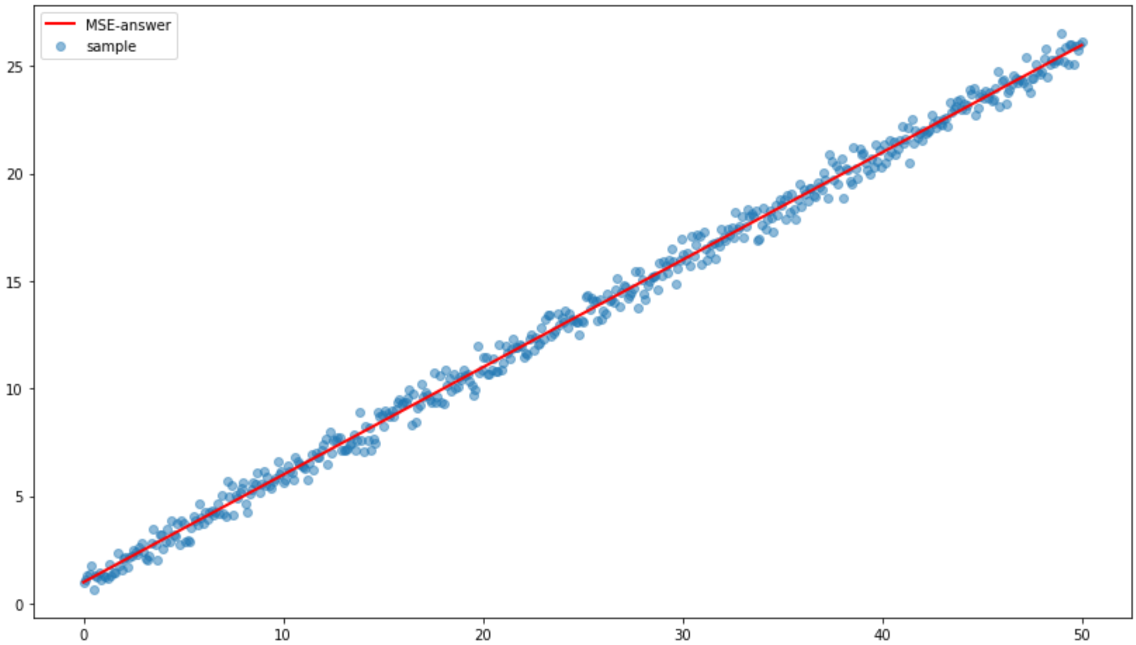
```
def mse(k, b, xs, sample):
    predicted = k * xs + b
    return metrics.mean_squared_error(sample, predicted)
```

In [9]:

```
k,b = optimize.minimize(lambda x: mse(x[0], x[1], xs, sample), (0, 0)).x
```

In [10]:

```
plt.figure(figsize=(14,8))
plt.scatter(xs, sample, alpha=0.5, label='sample')
plt.plot(xs, k * xs + b, c='red', linewidth=2, label='MSE-answer')
plt.legend()
plt.show()
```



In [11]:

```
print 'k = {}, b = {}'.format(k,b)
```

```
k = 0.499438841301, b = 0.992403024827
```

В выборке без выбросов восстановить прямую получилось очень хорошо

In [12]:

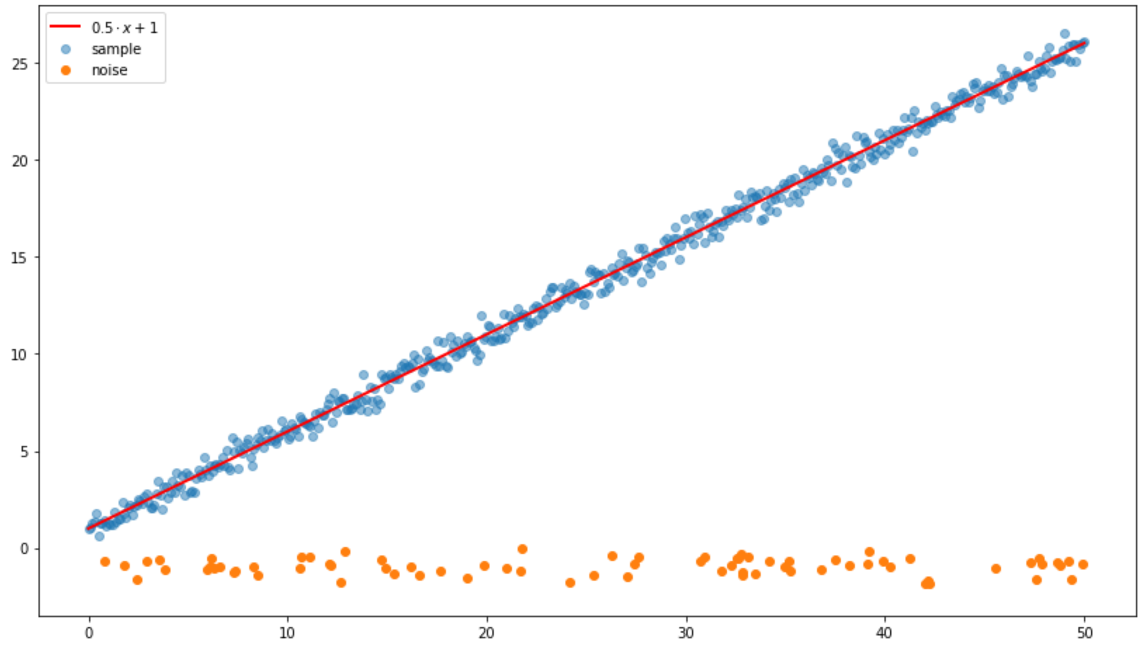
```
addictional_xs = stats.uniform(0, 50).rvs(75)
```

In [13]:

```
bad_points = -1 + stats.norm(scale=np.sqrt(0.2)).rvs(75)
```

In [14]:

```
plt.figure(figsize=(14,8))
plt.scatter(xs, sample, alpha=0.5, label='sample')
plt.plot(xs, 0.5 * xs + 1, c='red', linewidth=2, label='$0.5 \cdot x + 1$')
plt.scatter(addictional_xs, bad_points, label='noise')
plt.legend()
plt.show()
```



In [15]:

```
xs = np.append(xs, addictional_xs)
```

In [16]:

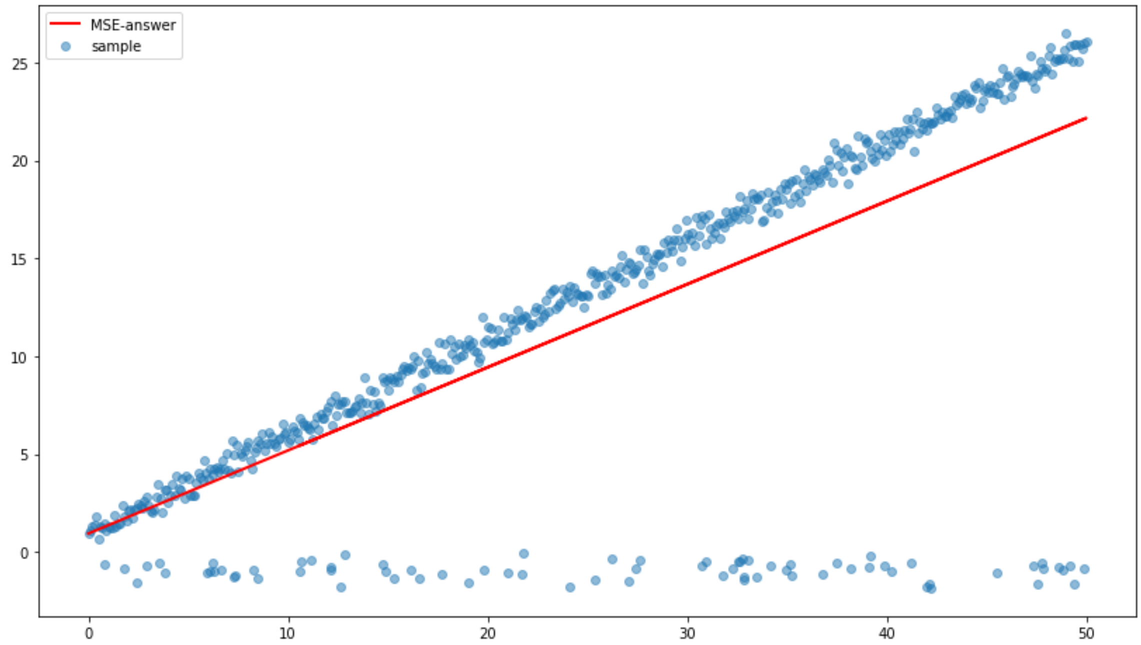
```
sample = np.append(sample, bad_points)
```

In [17]:

```
k_mse,b_mse = optimize.minimize(lambda x: mse(x[0], x[1], xs, sample), (0, 0)).x
```

In [18]:

```
plt.figure(figsize=(14,8))
plt.scatter(xs, sample, alpha=0.5, label='sample')
plt.plot(xs, k_mse * xs + b_mse, c='red', linewidth=2, label='MSE-answer')
plt.legend()
plt.show()
```



In [19]:

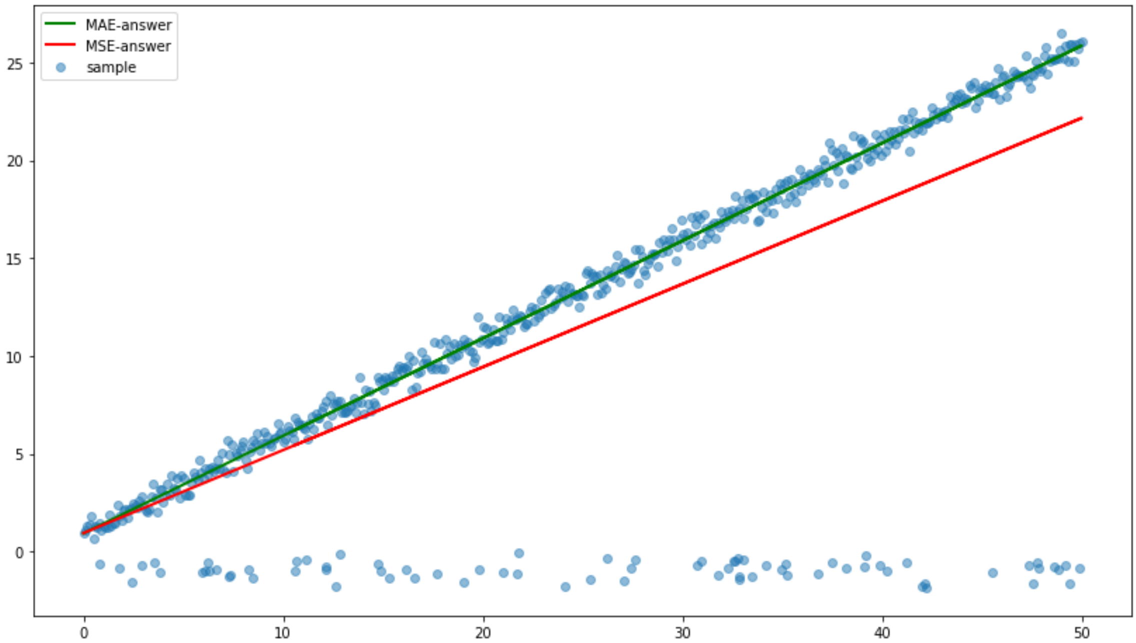
```
def mae(k, b, xs, sample):
    predicted = k * xs + b
    return metrics.mean_absolute_error(sample, predicted)
```

In [20]:

```
k_mae,b_mae = optimize.minimize(lambda x: mae(x[0], x[1], xs, sample), (0, 0)).x
```

In [21]:

```
plt.figure(figsize=(14,8))
plt.scatter(xs, sample, alpha=0.5, label='sample')
plt.plot(xs, k_mae * xs + b_mae, c='g', linewidth=2, label='MAE-answer')
plt.plot(xs, k_mse * xs + b_mse, c='r', linewidth=2, label='MSE-answer')
plt.legend()
plt.show()
```



Оптимизация MAE гораздо более устойчива к выбросам, чем оптимизация MSE, ведь медиана, которая оценивается при минимизации MAE, почти не сдвинется от добавления малого числа выбросов, в отличии от матожидания, которое оценивается при минимизации MSE.