swap_classifier(Jan14)

January 18, 2021

[1]:
```
import sys
quic_path = '/home/quic/QUIC-Projects'
if not quic_path in sys.path:
    sys.path.append(quic_path)
```

[2]:
```
from custom_qiskit_v3_2.datageneration import Toy2DLinearLoader, DataScaler,␣
↪DataMultiScaler
from custom_qiskit_v3_2.classifier import BinarySVM, Kernel
import numpy as np
from matplotlib import pyplot as plt
```

1 Is reduction of b critical?

lifted from https://www.elen.ucl.ac.be/Proceedings/esann/esannpdf/es2004-11.pdf said in classifying the MNIST data with Gaussian kernels, the value k = 10 proved to be a very good one justifying all the reasons for its introduction (fast learning, small number of support vectors and good generalization).

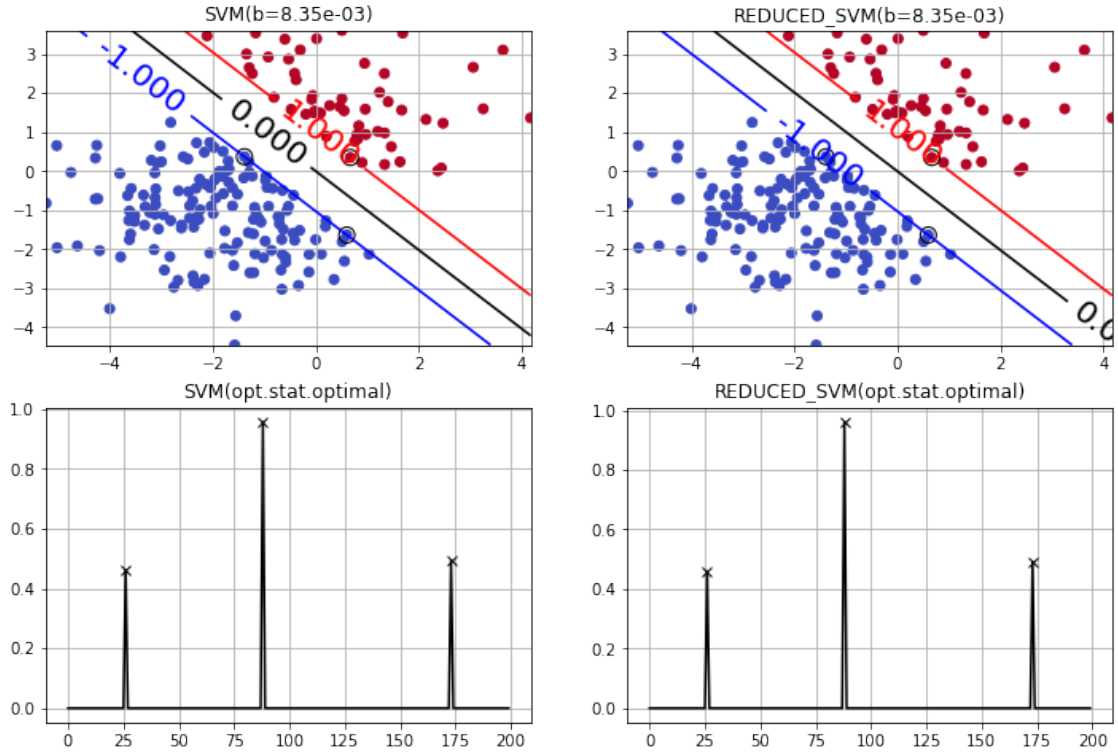
$$\frac{1}{2}||w||^2 \quad V.S. \quad \frac{1}{2}||w||^2 + \frac{k}{2}b^2$$

[3]:
```
# set hyperparams
C = None # infinite
kernel = Kernel('linear')
k = 1 # hyperparam for reduced svm
w = (1,1)
b = 0

# set svms
svm1 = BinarySVM(kernel, C, mutation='SVM')
svm2 = BinarySVM(kernel, C, mutation='REDUCED_SVM', k=k)
svm3 = BinarySVM(kernel, C, mutation='QASVM')
svm4 = BinarySVM(kernel, C, mutation='REDUCED_QASVM', k=k)

# load data
dataloader = Toy2DLinearLoader(w, b)
```

```
X, y = dataloader(200)
datascaler = DataScaler('standard')

# fit
svm1.fit(X, y)
svm2.fit(X, y)
print(svm1)
print(svm2)
```

```
BinarySVM: (SVM)
        Kernel: linear
        HyperParameter: None
        Optimization Status: optimal
        Iterations: 8

BinarySVM: (REDUCED_SVM)
        Kernel: linear
        HyperParameter: None
        Optimization Status: optimal
        Iterations: 8
```

[4]:
```
# visualization
fig, axes = plt.subplots(2, 2, figsize=(12,8))
svms = [svm1, svm2]
for i in range(2):
    svms[i].plot_boundary(ax=axes[0,i])
    svms[i].plot('alpha', ax=axes[1,i])
    axes[0,i].set_title('{:}(b={:.2e})'.format(svms[i].mutation, svms[i].b))
    axes[1,i].set_title('{:}(opt.stat.{:})'.format(svms[i].mutation, svms[i].
 ↪status))

plt.savefig('./figs/hardmargin_zerobias.png')
```



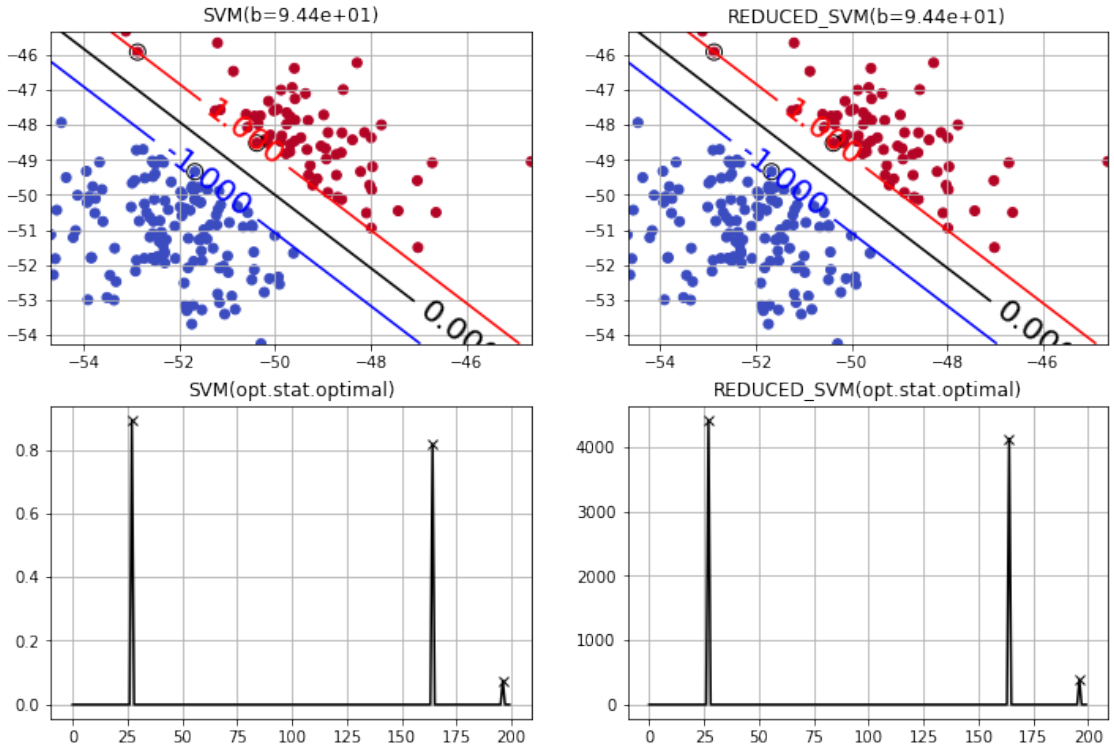
1.1 what if b is non-zero?

[5]:
```
# set hyperparams
C = None # infinite
kernel = Kernel('linear')
k = 1 # hyperparam for reduced svm
w = (1,1)
b = 1e2

# set svms
svm1 = BinarySVM(kernel, C, mutation='SVM')
svm2 = BinarySVM(kernel, C, mutation='REDUCED_SVM', k=k)
svm3 = BinarySVM(kernel, C, mutation='QASVM')
svm4 = BinarySVM(kernel, C, mutation='REDUCED_QASVM', k=k)

# load data
dataloader = Toy2DLinearLoader(w, b)
X, y = dataloader(200)
datascaler = DataScaler('standard')

# fit
svm1.fit(X, y)
svm2.fit(X, y)
```

```
print(svm1)
print(svm2)
```

```
BinarySVM: (SVM)
        Kernel: linear
        HyperParameter: None
        Optimization Status: optimal
        Iterations: 9

BinarySVM: (REDUCED_SVM)
        Kernel: linear
        HyperParameter: None
        Optimization Status: optimal
        Iterations: 11
```

[6]:
```
# visualization
fig, axes = plt.subplots(2, 2, figsize=(12,8))
svms = [svm1, svm2]
for i in range(2):
    svms[i].plot_boundary(ax=axes[0,i])
    svms[i].plot('alpha', ax=axes[1,i])
    axes[0,i].set_title('{:}(b={:.2e})'.format(svms[i].mutation, svms[i].b))
    axes[1,i].set_title('{:}(opt.stat.{:})'.format(svms[i].mutation, svms[i].
 ↪status))

plt.savefig('./figs/hardmargin_nonzerobias.png')
```



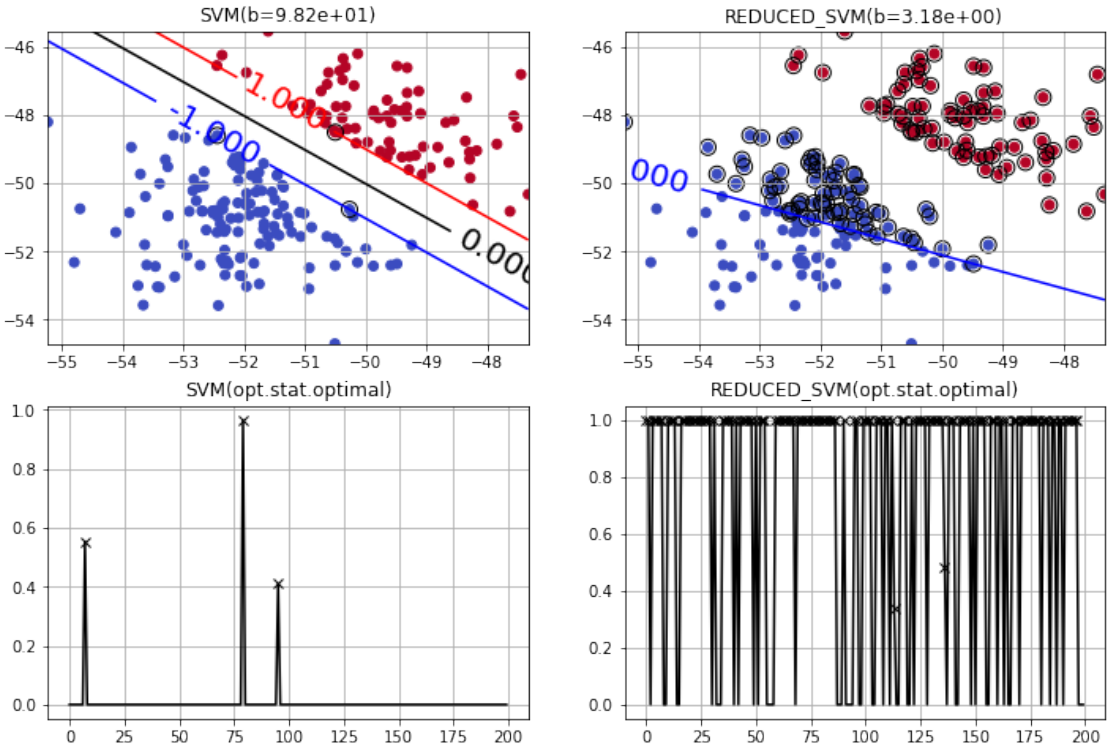
1.2 what if it is not hardmargin?

[7]:
```
# set hyperparams
C = 1 # infinite
kernel = Kernel('linear')
k = 1 # hyperparam for reduced svm
w = (1,1)
b = 1e2

# set svms
svm1 = BinarySVM(kernel, C, mutation='SVM')
svm2 = BinarySVM(kernel, C, mutation='REDUCED_SVM', k=k)
svm3 = BinarySVM(kernel, C, mutation='QASVM')
svm4 = BinarySVM(kernel, C, mutation='REDUCED_QASVM', k=k)

# load data
dataloader = Toy2DLinearLoader(w, b)
X, y = dataloader(200)
datascaler = DataScaler('standard')

# fit
svm1.fit(X, y)
svm2.fit(X, y)
```

```
print(svm1)
print(svm2)
```

```
BinarySVM: (SVM)
        Kernel: linear
        HyperParameter: 1
        Optimization Status: optimal
        Iterations: 10

BinarySVM: (REDUCED_SVM)
        Kernel: linear
        HyperParameter: 1
        Optimization Status: optimal
        Iterations: 11
```

[8]:
```
# visualization
fig, axes = plt.subplots(2, 2, figsize=(12,8))
svms = [svm1, svm2]
for i in range(2):
    svms[i].plot_boundary(ax=axes[0,i])
    svms[i].plot('alpha', ax=axes[1,i])
    axes[0,i].set_title('{:}(b={:.2e})'.format(svms[i].mutation, svms[i].b))
    axes[1,i].set_title('{:}(opt.stat.{:})'.format(svms[i].mutation, svms[i].
 ↪status))

plt.savefig('./figs/softmargin_nonzerobias.png')
```



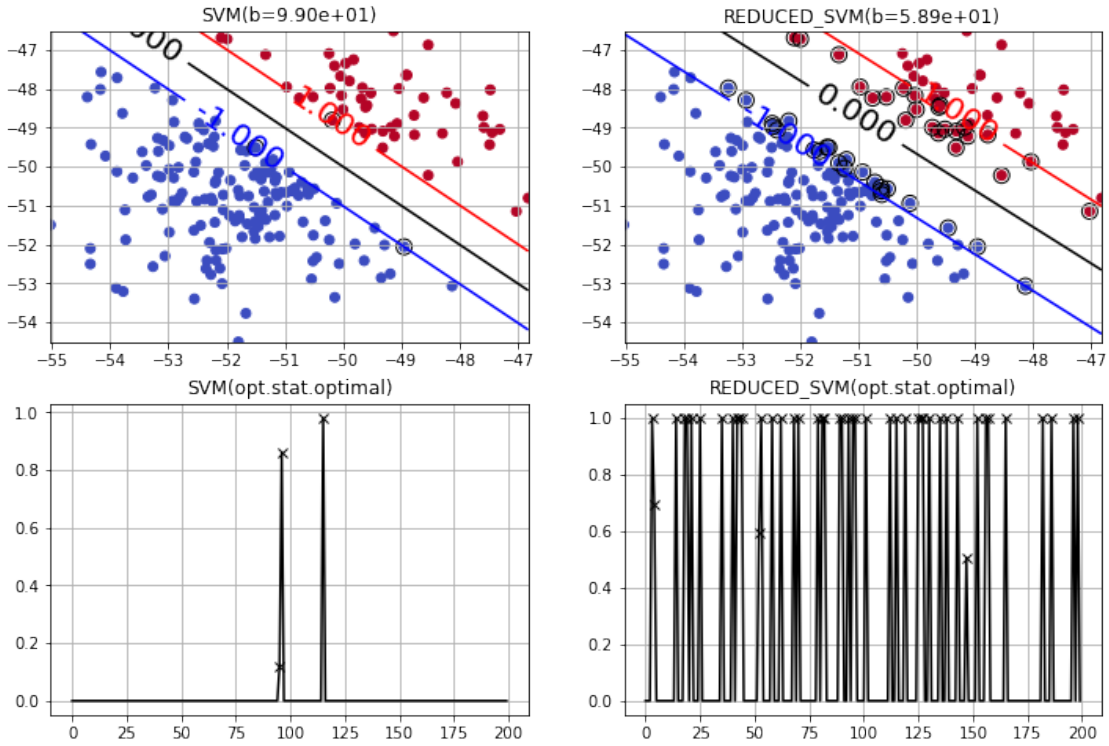
1.3 what if decrease impact of b?

[9]:
```
# set hyperparams
C = 1 # infinite
kernel = Kernel('linear')
k = 1e-2 # hyperparam for reduced svm
w = (1,1)
b = 1e2

# set svms
svm1 = BinarySVM(kernel, C, mutation='SVM')
svm2 = BinarySVM(kernel, C, mutation='REDUCED_SVM', k=k)
svm3 = BinarySVM(kernel, C, mutation='QASVM')
svm4 = BinarySVM(kernel, C, mutation='REDUCED_QASVM', k=k)

# load data
dataloader = Toy2DLinearLoader(w, b)
X, y = dataloader(200)
datascaler = DataScaler('standard')

# fit
svm1.fit(X, y)
svm2.fit(X, y)
```

```
print(svm1)
print(svm2)
```

```
BinarySVM: (SVM)
        Kernel: linear
        HyperParameter: 1
        Optimization Status: optimal
        Iterations: 11

BinarySVM: (REDUCED_SVM)
        Kernel: linear
        HyperParameter: 1
        Optimization Status: optimal
        Iterations: 11
```

[10]:
```
# visualization
fig, axes = plt.subplots(2, 2, figsize=(12,8))
svms = [svm1, svm2]
for i in range(2):
    svms[i].plot_boundary(ax=axes[0,i])
    svms[i].plot('alpha', ax=axes[1,i])
    axes[0,i].set_title('{:}(b={:.2e})'.format(svms[i].mutation, svms[i].b))
    axes[1,i].set_title('{:}(opt.stat.{:})'.format(svms[i].mutation, svms[i].
 ↪status))

plt.savefig('./figs/softmargin_nonzerobias_smallk.png')
```



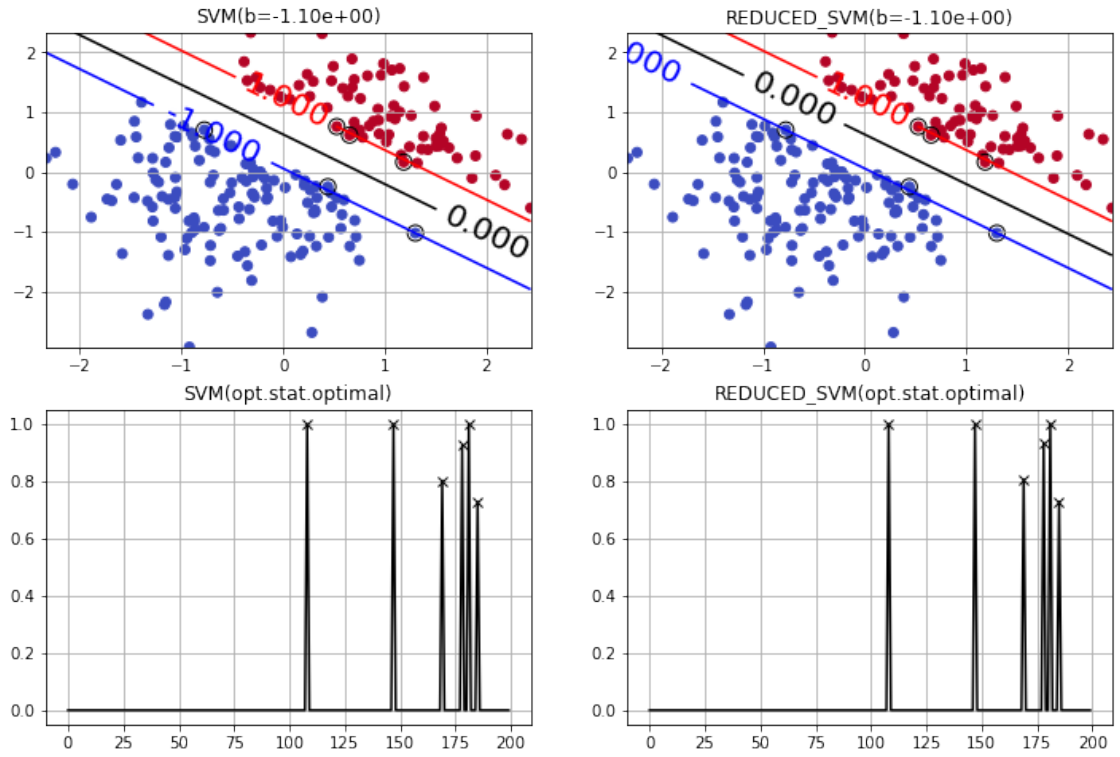
1.4 what if standardrize data?(standard)

[11]:
```
# set hyperparams
C = 1 # infinite
kernel = Kernel('linear')
k = 1e-2 # hyperparam for reduced svm
w = (1,1)
b = 1e2

# set svms
svm1 = BinarySVM(kernel, C, mutation='SVM')
svm2 = BinarySVM(kernel, C, mutation='REDUCED_SVM', k=k)
svm3 = BinarySVM(kernel, C, mutation='QASVM')
svm4 = BinarySVM(kernel, C, mutation='REDUCED_QASVM', k=k)

# load data
dataloader = Toy2DLinearLoader(w, b)
X, y = dataloader(200)
datascaler = DataScaler('standard')

# fit
svm1.fit(datascaler(X), y)
svm2.fit(datascaler(X), y)
```

```
print(svm1)
print(svm2)
```

```
BinarySVM: (SVM)
        Kernel: linear
        HyperParameter: 1
        Optimization Status: optimal
        Iterations: 15

BinarySVM: (REDUCED_SVM)
        Kernel: linear
        HyperParameter: 1
        Optimization Status: optimal
        Iterations: 15
```

[12]:
```
# visualization
fig, axes = plt.subplots(2, 2, figsize=(12,8))
svms = [svm1, svm2]
for i in range(2):
    svms[i].plot_boundary(ax=axes[0,i])
    svms[i].plot('alpha', ax=axes[1,i])
    axes[0,i].set_title('{:}(b={:.2e})'.format(svms[i].mutation, svms[i].b))
    axes[1,i].set_title('{:}(opt.stat.{:})'.format(svms[i].mutation, svms[i].
 ↪status))

plt.savefig('./figs/zeromean.png')
```



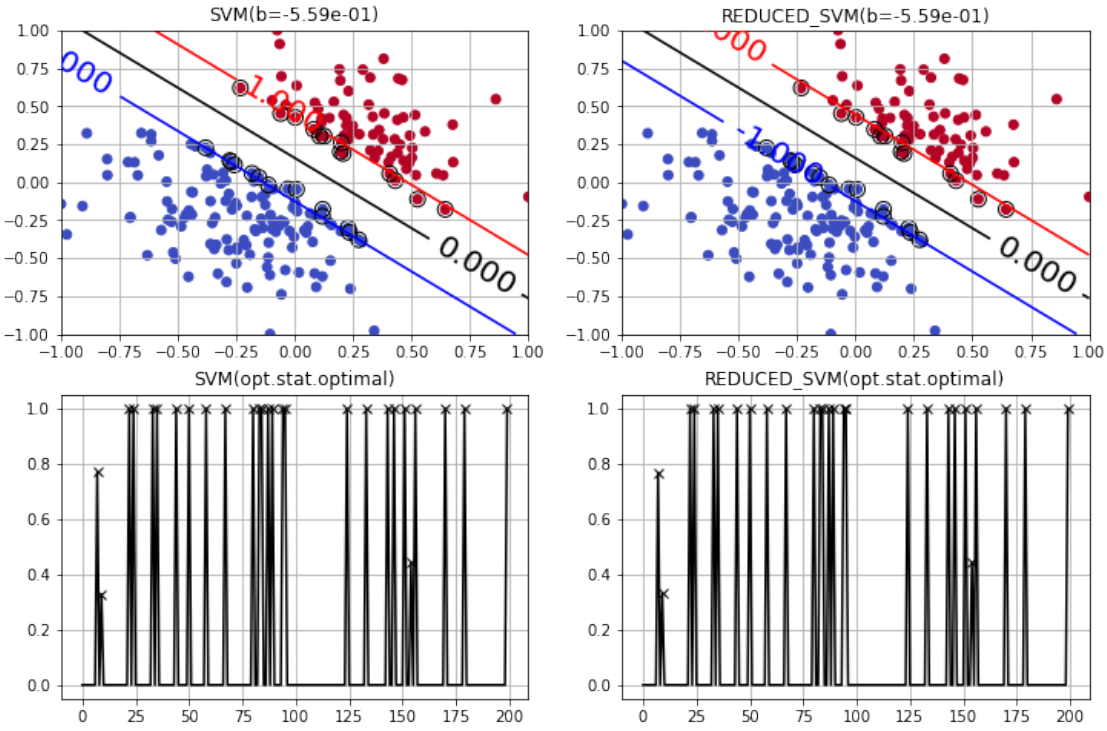
1.5 what if standardrize data?(maxabs)

[13]:
```
# set hyperparams
C = 1 # infinite
kernel = Kernel('linear')
k = 1e-2 # hyperparam for reduced svm
w = (1,1)
b = 1e2

# set svms
svm1 = BinarySVM(kernel, C, mutation='SVM')
svm2 = BinarySVM(kernel, C, mutation='REDUCED_SVM', k=k)
svm3 = BinarySVM(kernel, C, mutation='QASVM')
svm4 = BinarySVM(kernel, C, mutation='REDUCED_QASVM', k=k)

# load data
dataloader = Toy2DLinearLoader(w, b)
X, y = dataloader(200)
datascaler = DataScaler('minmax', feature_range=(-1,1))

# fit
svm1.fit(datascaler(X), y)
```

```
svm2.fit(datascaler(X), y)
print(svm1)
print(svm2)
```

```
BinarySVM: (SVM)
        Kernel: linear
        HyperParameter: 1
        Optimization Status: optimal
        Iterations: 11

BinarySVM: (REDUCED_SVM)
        Kernel: linear
        HyperParameter: 1
        Optimization Status: optimal
        Iterations: 11
```

[14]:
```
# visualization
fig, axes = plt.subplots(2, 2, figsize=(12,8))
svms = [svm1, svm2]
for i in range(2):
    svms[i].plot_boundary(ax=axes[0,i])
    svms[i].plot('alpha', ax=axes[1,i])
    axes[0,i].set_title('{:}(b={:.2e})'.format(svms[i].mutation, svms[i].b))
    axes[1,i].set_title('{:}(opt.stat.{:})'.format(svms[i].mutation, svms[i].
 ↪status))

plt.savefig('./figs/maxabs.png')
```



1.6 Conclusion

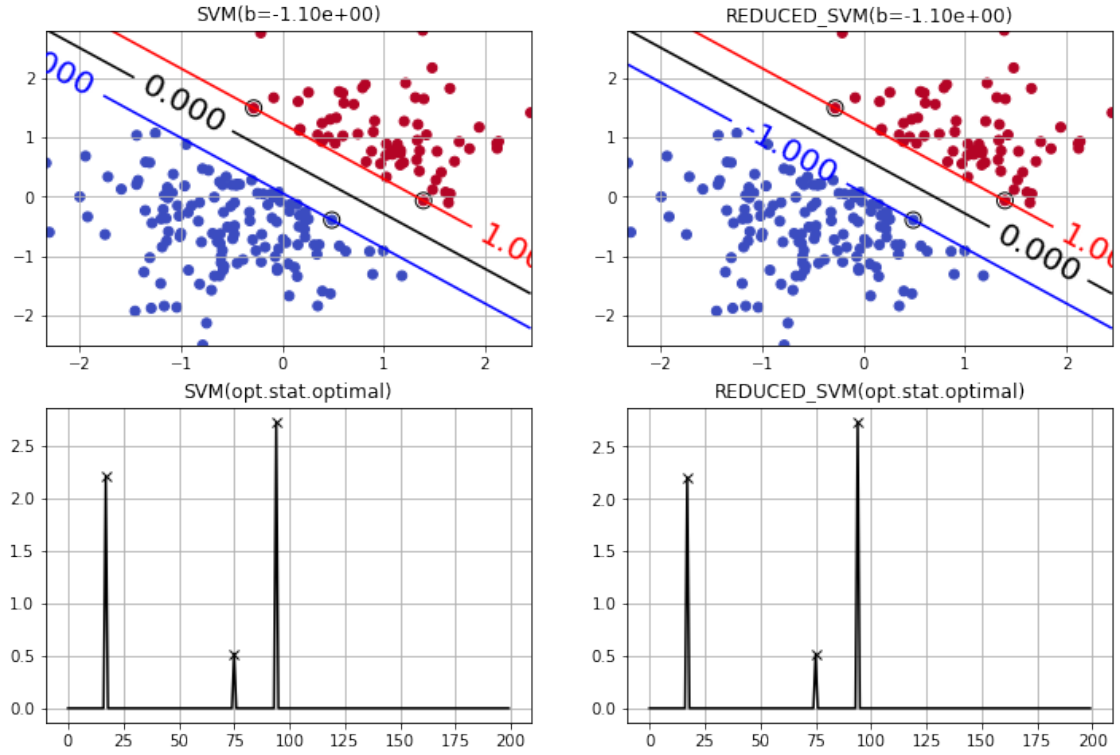
1. scale data
2. reduced impact of b
3. inspect hard margin

[15]:
```
# set hyperparams
C = 100 # infinite
kernel = Kernel('linear')
k = 1e-2 # hyperparam for reduced svm
w = (1,1)
b = 1e2

# set svms
svm1 = BinarySVM(kernel, C, mutation='SVM')
svm2 = BinarySVM(kernel, C, mutation='REDUCED_SVM', k=k)
svm3 = BinarySVM(kernel, C, mutation='QASVM')
svm4 = BinarySVM(kernel, C, mutation='REDUCED_QASVM', k=k)

# load data
dataloader = Toy2DLinearLoader(w, b)
X, y = dataloader(200)
datascaler = DataScaler('standard')
```

```
# fit
svm1.fit(datascaler(X), y)
svm2.fit(datascaler(X), y)
print(svm1)
print(svm2)
```

```
BinarySVM: (SVM)
        Kernel: linear
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 12

BinarySVM: (REDUCED_SVM)
        Kernel: linear
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 12
```

[16]:
```
# visualization
fig, axes = plt.subplots(2, 2, figsize=(12,8))
svms = [svm1, svm2]
for i in range(2):
    svms[i].plot_boundary(ax=axes[0,i])
    svms[i].plot('alpha', ax=axes[1,i])
    axes[0,i].set_title('{:}(b={:.2e})'.format(svms[i].mutation, svms[i].b))
    axes[1,i].set_title('{:}(opt.stat.{:})'.format(svms[i].mutation, svms[i].
 ↪status))

plt.savefig('./figs/conclustion_on_reduced_svm.png')
```



2 Different Kernels

1. Amplitude Encoding $\langle|x\rangle = \frac{1}{||x||}\sum_{i=0}^{2^n-1} x_i \langle|i\rangle \Rightarrow k(x,y) = |\langle x|y\rangle|^2$ Pow2 kernel
2. Phase Encoding $\langle|x\rangle = \frac{1}{\sqrt{N}}\sum_{i=0}^{2^n-1} e^{jx_i}\langle|i\rangle \Rightarrow k(x,y) = [\sum\cos(x_i - y_i)]^2 + [\sum\sin(x_i - y_i)]^2$ Phase kernel
3. Angle Encoding $\langle|x\rangle = \otimes_{i=0}^{2^n-1}[\cos(x_i)\langle|0\rangle + \sin(x_i)\langle|1\rangle] \Rightarrow k(x,y) = \prod\cos(x_i - y_i)^2$ Cosine kernel
4. Coherent Encoding $\langle|x\rangle = \otimes_{i=0}^{2^n-1}\langle|\alpha_{x_i}\rangle \Rightarrow k(x,y) = e^{-||x-y||^2}$ RBF kernel

2.1 Reduced SVM

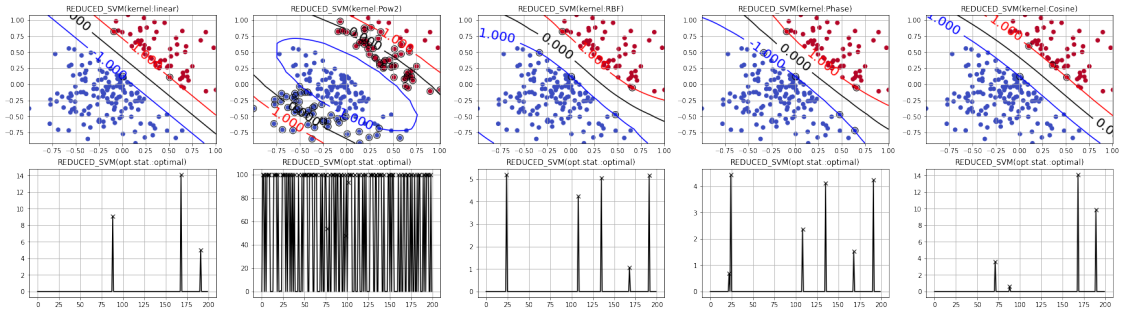
[17]:
```
# set hyperparams
C = 100 # infinite
k = 1e-2 # hyperparam for reduced svm
w = (1,1)
b = 1e2

# set sums
mutation = 'REDUCED_SVM'
svm1 = BinarySVM(Kernel('linear'), C, mutation=mutation, k=k)
svm1_1 = BinarySVM(Kernel('Pow2'), C, mutation=mutation, k=k)
svm2 = BinarySVM(Kernel('RBF', 2), C, mutation=mutation, k=k)
```

```
svm3 = BinarySVM(Kernel('Phase'), C, mutation=mutation, k=k)
svm4 = BinarySVM(Kernel('Cosine'), C, mutation=mutation, k=k)

# load data
dataloader = Toy2DLinearLoader(w, b)
X, y = dataloader(200)
datascaler1 = DataScaler('maxabs')
datascaler2 = DataScaler('standard', with_std=False)
datascaler = DataMultiScaler(datascaler1, datascaler2)

# fit
svm1.fit(datascaler(X), y)
svm1_1.fit(datascaler(X), y)
svm2.fit(datascaler(X), y)
svm3.fit(datascaler(X), y)
svm4.fit(datascaler(X), y)
print(svm1, svm1_1, svm2, svm3, svm4)
```

```
BinarySVM: (REDUCED_SVM)
        Kernel: linear
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 12
 BinarySVM: (REDUCED_SVM)
        Kernel: Pow2
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 16
 BinarySVM: (REDUCED_SVM)
        Kernel: RBF
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 12
 BinarySVM: (REDUCED_SVM)
        Kernel: Phase
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 13
 BinarySVM: (REDUCED_SVM)
        Kernel: Cosine
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 13
```

[18]:
```
# visualization
fig, axes = plt.subplots(2,5, figsize=(30,8))
```

```
svms = [svm1, svm1_1, svm2, svm3, svm4]
for i in range(len(svms)):
    svms[i].plot_boundary(ax=axes[0,i])
    svms[i].plot('alpha', ax=axes[1,i])
    axes[0,i].set_title('{:}(kernel:{:})'.format(svms[i].mutation, svms[i].
 ↪kernel))
    axes[1,i].set_title('{:}(opt.stat.:{:})'.format(svms[i].mutation, svms[i].
 ↪status))

plt.savefig('./figs/reduced_svm_kernels.png')
```



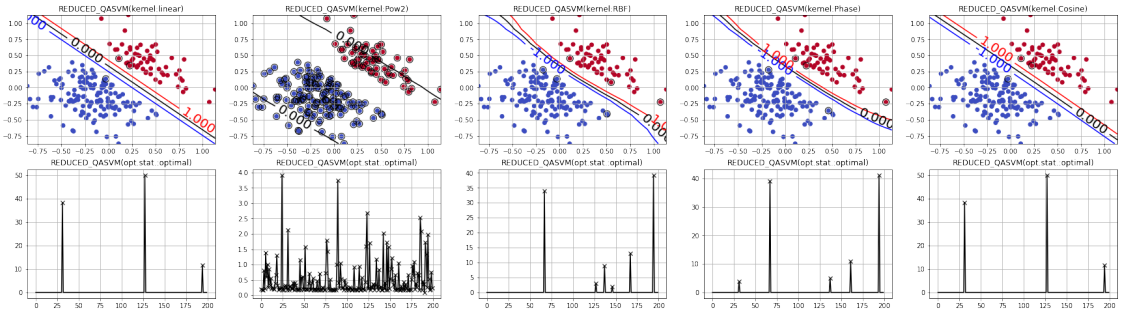
2.2 Reduced QASVM

[19]:
```
# set hyperparams
C = 100 # infinite
k = 1e-2 # hyperparam for reduced svm
w = (1,1)
b = 1e2

# set sums
mutation = 'REDUCED_QASVM'
svm1 = BinarySVM(Kernel('linear'), C, mutation=mutation, k=k)
svm1_1 = BinarySVM(Kernel('Pow2'), C, mutation=mutation, k=k)
svm2 = BinarySVM(Kernel('RBF', 2), C, mutation=mutation, k=k)
svm3 = BinarySVM(Kernel('Phase'), C, mutation=mutation, k=k)
svm4 = BinarySVM(Kernel('Cosine'), C, mutation=mutation, k=k)

# load data
dataloader = Toy2DLinearLoader(w, b)
X, y = dataloader(200)
datascaler1 = DataScaler('maxabs')
datascaler2 = DataScaler('standard', with_std=False)
datascaler = DataMultiScaler(datascaler1, datascaler2)

# fit
```

```
svm1.fit(datascaler(X), y)
svm1_1.fit(datascaler(X), y)
svm2.fit(datascaler(X), y)
svm3.fit(datascaler(X), y)
svm4.fit(datascaler(X), y)
print(svm1, svm1_1, svm2, svm3, svm4)
```

```
BinarySVM: (REDUCED_QASVM)
        Kernel: linear
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 8
 BinarySVM: (REDUCED_QASVM)
        Kernel: Pow2
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 5
 BinarySVM: (REDUCED_QASVM)
        Kernel: RBF
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 7
 BinarySVM: (REDUCED_QASVM)
        Kernel: Phase
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 8
 BinarySVM: (REDUCED_QASVM)
        Kernel: Cosine
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 8
```

[20]:
```
# visualization
fig, axes = plt.subplots(2,5, figsize=(30,8))
svms = [svm1, svm1_1, svm2, svm3, svm4]
for i in range(len(svms)):
    svms[i].plot_boundary(ax=axes[0,i])
    svms[i].plot('alpha', ax=axes[1,i])
    axes[0,i].set_title('{:}(kernel:{:})'.format(svms[i].mutation, svms[i].
 ↪kernel))
    axes[1,i].set_title('{:}(opt.stat.:{:})'.format(svms[i].mutation, svms[i].
 ↪status))

plt.savefig('./figs/reduced_qasvm_kernels.png')
```



3 About primal SVM methods,

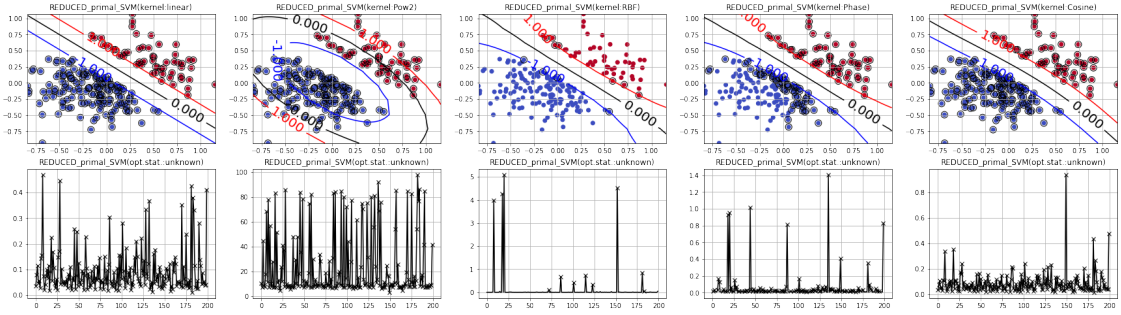
3.1 Reduced primal SVM

[21]:
```
# set hyperparams
C = 100 # infinite
k = 1e-2 # hyperparam for reduced svm
w = (1,1)
b = 1e2

# set svms
mutation = 'REDUCED_primal_SVM'
svm1 = BinarySVM(Kernel('linear'), C, mutation=mutation, k=k)
svm1_1 = BinarySVM(Kernel('Pow2'), C, mutation=mutation, k=k)
svm2 = BinarySVM(Kernel('RBF', 2), C, mutation=mutation, k=k)
svm3 = BinarySVM(Kernel('Phase'), C, mutation=mutation, k=k)
svm4 = BinarySVM(Kernel('Cosine'), C, mutation=mutation, k=k)

# load data
dataloader = Toy2DLinearLoader(w, b)
X, y = dataloader(200)
datascaler1 = DataScaler('maxabs')
datascaler2 = DataScaler('standard', with_std=False)
datascaler = DataMultiScaler(datascaler1, datascaler2)

# fit
svm1.fit(datascaler(X), y)
svm1_1.fit(datascaler(X), y)
svm2.fit(datascaler(X), y)
svm3.fit(datascaler(X), y)
svm4.fit(datascaler(X), y)
print(svm1, svm1_1, svm2, svm3, svm4)
```

```
BinarySVM: (REDUCED_primal_SVM)
        Kernel: linear
```

```
        HyperParameter: 100
        Optimization Status: unknown
        Iterations: 11
BinarySVM: (REDUCED_primal_SVM)
        Kernel: Pow2
        HyperParameter: 100
        Optimization Status: unknown
        Iterations: 13
BinarySVM: (REDUCED_primal_SVM)
        Kernel: RBF
        HyperParameter: 100
        Optimization Status: unknown
        Iterations: 18
BinarySVM: (REDUCED_primal_SVM)
        Kernel: Phase
        HyperParameter: 100
        Optimization Status: unknown
        Iterations: 16
BinarySVM: (REDUCED_primal_SVM)
        Kernel: Cosine
        HyperParameter: 100
        Optimization Status: unknown
        Iterations: 12
```

[22]:
```
# visualization
fig, axes = plt.subplots(2,5, figsize=(30,8))
svms = [svm1, svm1_1, svm2, svm3, svm4]
for i in range(len(svms)):
    svms[i].plot_boundary(ax=axes[0,i])
    svms[i].plot('alpha', ax=axes[1,i])
    axes[0,i].set_title('{:}(kernel:{:})'.format(svms[i].mutation, svms[i].
 ↪kernel))
    axes[1,i].set_title('{:}(opt.stat.:{:})'.format(svms[i].mutation, svms[i].
 ↪status))

plt.savefig('./figs/reduced_primal_svm_kernels.png')
```



3.2 Reduced primal QASVM

[23]:
```
# set hyperparams
C = 100 # infinite
k = 1e-2 # hyperparam for reduced svm
w = (1,1)
b = 1e2

# set svms
mutation = 'REDUCED_primal_QASVM'
svm1 = BinarySVM(Kernel('linear'), C, mutation=mutation, k=k)
svm1_1 = BinarySVM(Kernel('Pow2'), C, mutation=mutation, k=k)
svm2 = BinarySVM(Kernel('RBF', 2), C, mutation=mutation, k=k)
svm3 = BinarySVM(Kernel('Phase'), C, mutation=mutation, k=k)
svm4 = BinarySVM(Kernel('Cosine'), C, mutation=mutation, k=k)

# load data
dataloader = Toy2DLinearLoader(w, b)
X, y = dataloader(200)
datascaler1 = DataScaler('maxabs')
datascaler2 = DataScaler('standard', with_std=False)
datascaler = DataMultiScaler(datascaler1, datascaler2)

# fit
svm1.fit(datascaler(X), y)
svm1_1.fit(datascaler(X), y)
svm2.fit(datascaler(X), y)
svm3.fit(datascaler(X), y)
svm4.fit(datascaler(X), y)
print(svm1, svm1_1, svm2, svm3, svm4)
```

```
BinarySVM: (REDUCED_primal_QASVM)
        Kernel: linear
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 15
 BinarySVM: (REDUCED_primal_QASVM)
        Kernel: Pow2
        HyperParameter: 100
        Optimization Status: unknown
        Iterations: 15
 BinarySVM: (REDUCED_primal_QASVM)
        Kernel: RBF
        HyperParameter: 100
        Optimization Status: optimal
```

```
        Iterations: 15
BinarySVM: (REDUCED_primal_QASVM)
        Kernel: Phase
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 14
BinarySVM: (REDUCED_primal_QASVM)
        Kernel: Cosine
        HyperParameter: 100
        Optimization Status: optimal
        Iterations: 15
```

[24]:
```
# visualization
fig, axes = plt.subplots(2,5, figsize=(30,8))
svms = [svm1, svm1_1, svm2, svm3, svm4]
for i in range(len(svms)):
    svms[i].plot_boundary(ax=axes[0,i])
    svms[i].plot('alpha', ax=axes[1,i])
    axes[0,i].set_title('{:}(kernel:{:})'.format(svms[i].mutation, svms[i].
 ↪kernel))
    axes[1,i].set_title('{:}(opt.stat.:{:})'.format(svms[i].mutation, svms[i].
 ↪status))

plt.savefig('./figs/reduced_primal_qasvm_kernels.png')
```