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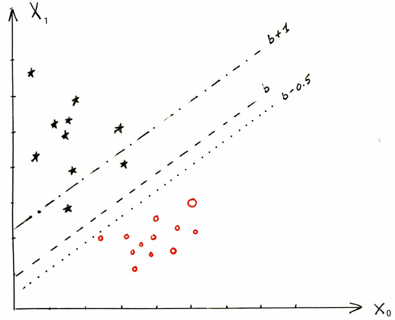

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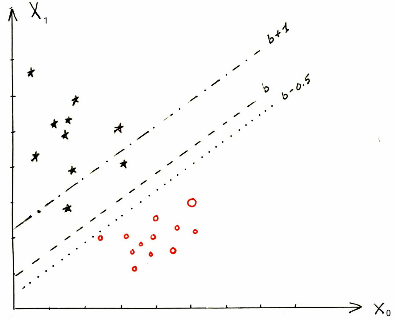

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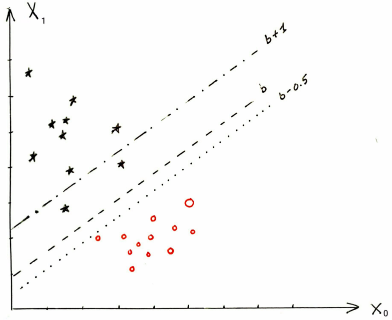

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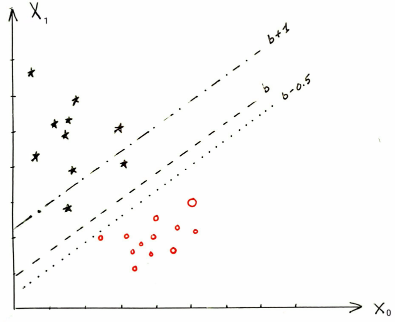

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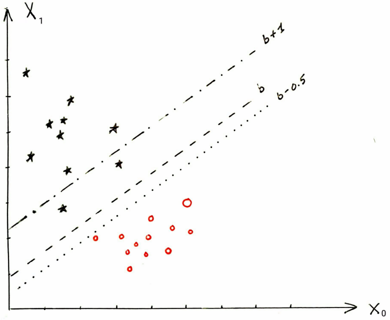

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- **Question: lines with 3 values of b are shown. Which is the best?**

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6. Ranking losses, etc, etc...

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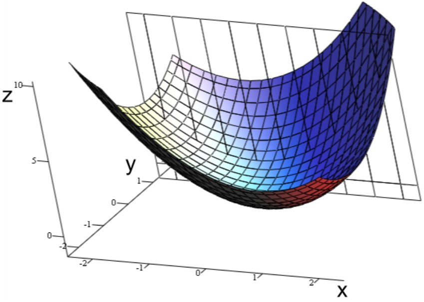
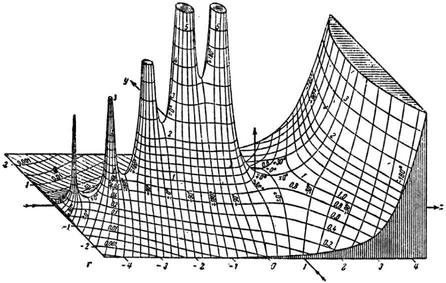
- Common regularization terms:
  1. L_2 norm (*Gaussian prior* or *weight decay*);
  2. L_1 norm (*sparse prior* or *lasso*)

Error surface

Error surfaces of convex and not-convex functions:



Convex function



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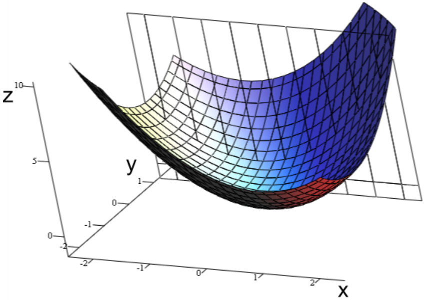

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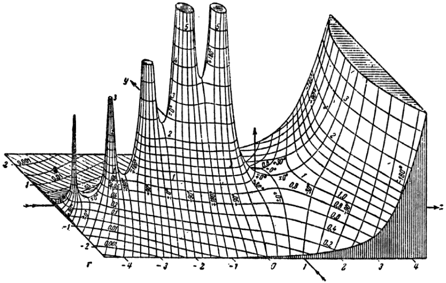

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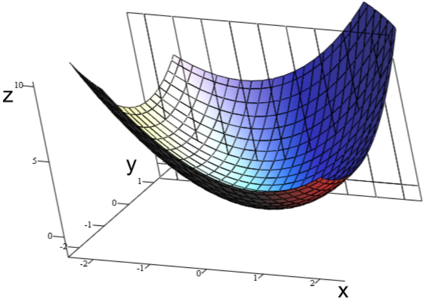

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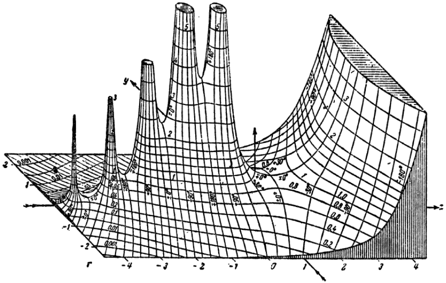

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- Linear and log-linear models as a rule have convex error functions.

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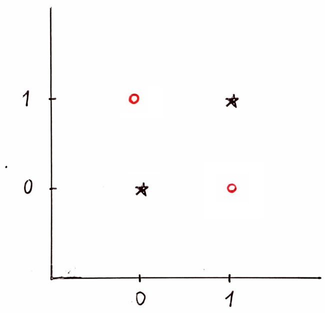

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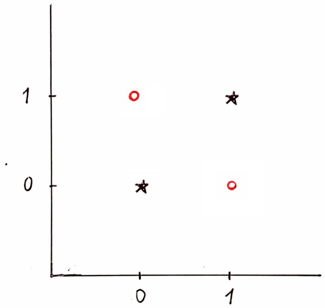

It is clearly not linearly separable.

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For example, $\phi(x_1, x_2) = [x_1 + x_2, x_1 \times x_2]$ maps the instances to another representation and makes the XOR problem linearly separable: