Machine Learning in Imaging

BME 590L
Roarke Horstmeyer

Lecture 4: A gentle introduction to optimization

Mathematical Optimization: "Selection of a best element (with regard to some criterion) from a set of available alternatives"

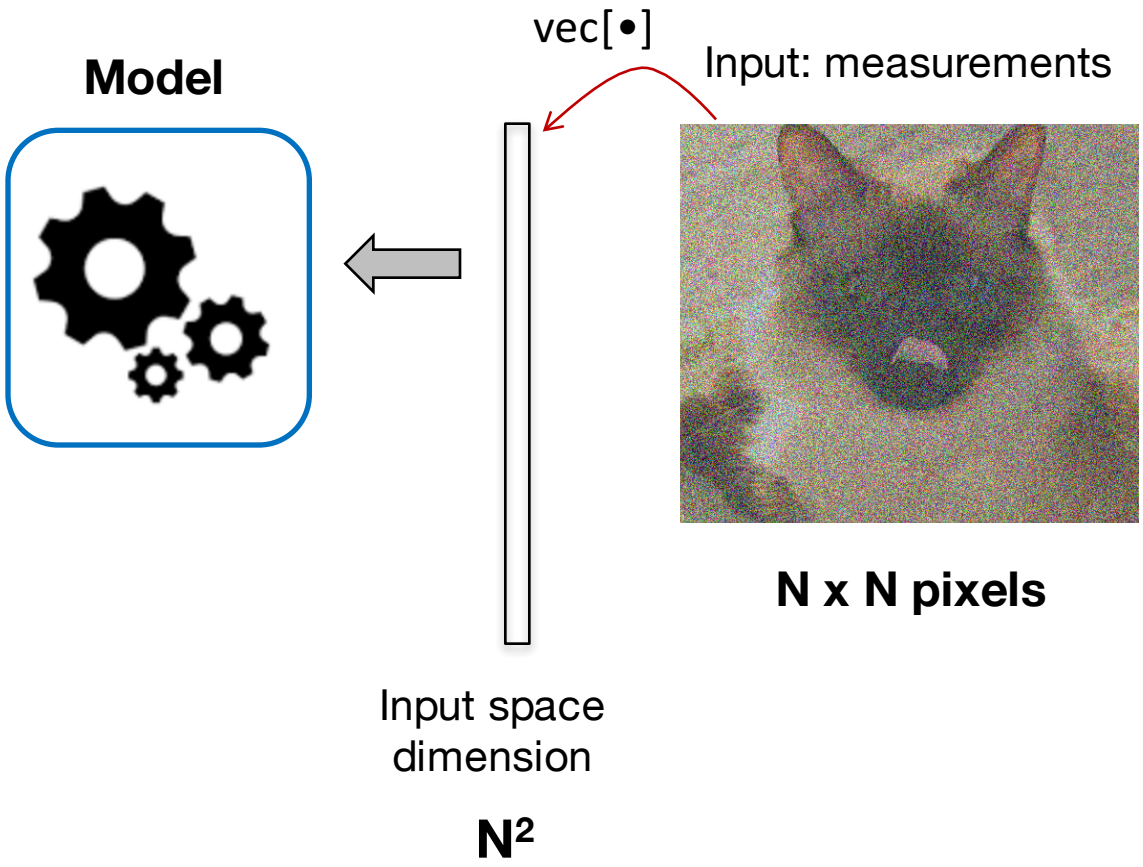
3 elements:

1) Your desired output (a better image, a clean signal, a classification of "cat" or "dog", etc.)

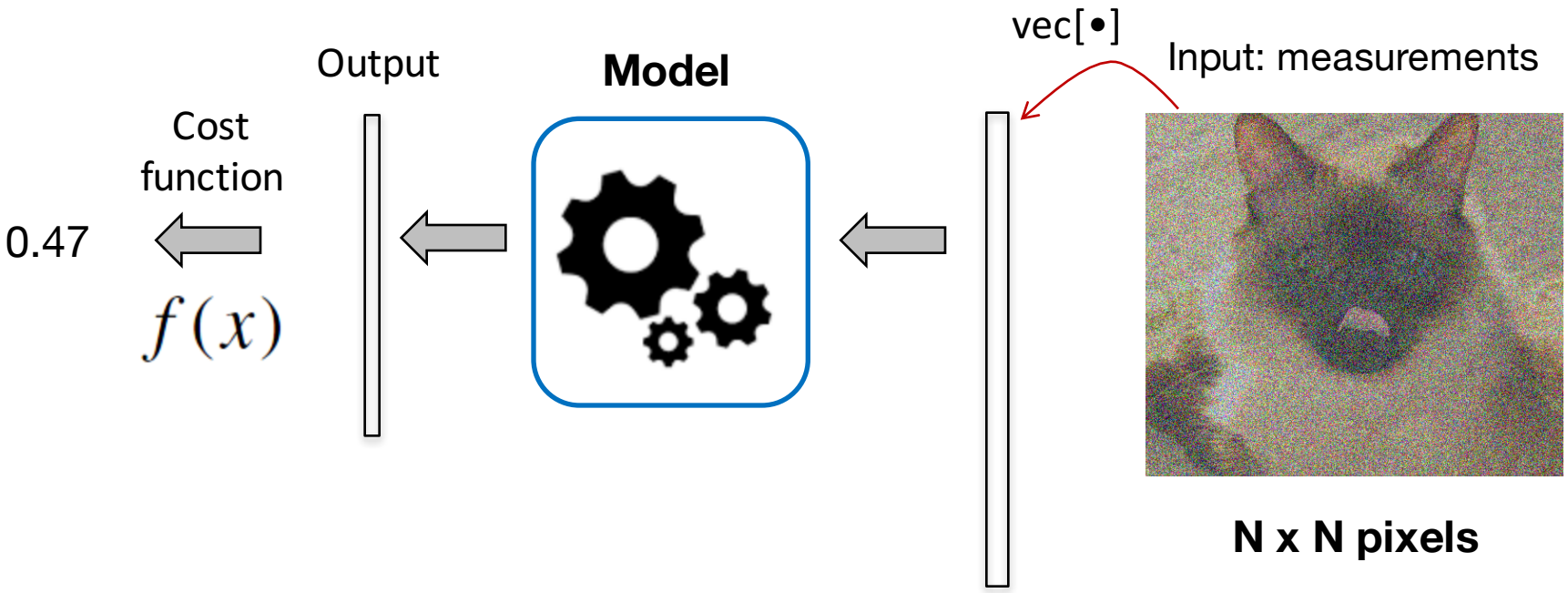
2) A model of what you are looking for - how you form the desired output from your measured data

3) A cost function, to measure how close you're getting to the answer (the cost function minimum)

Generalized optimization pipeline



Generalized optimization pipeline



Performance measure

1 number!

Output space dimension

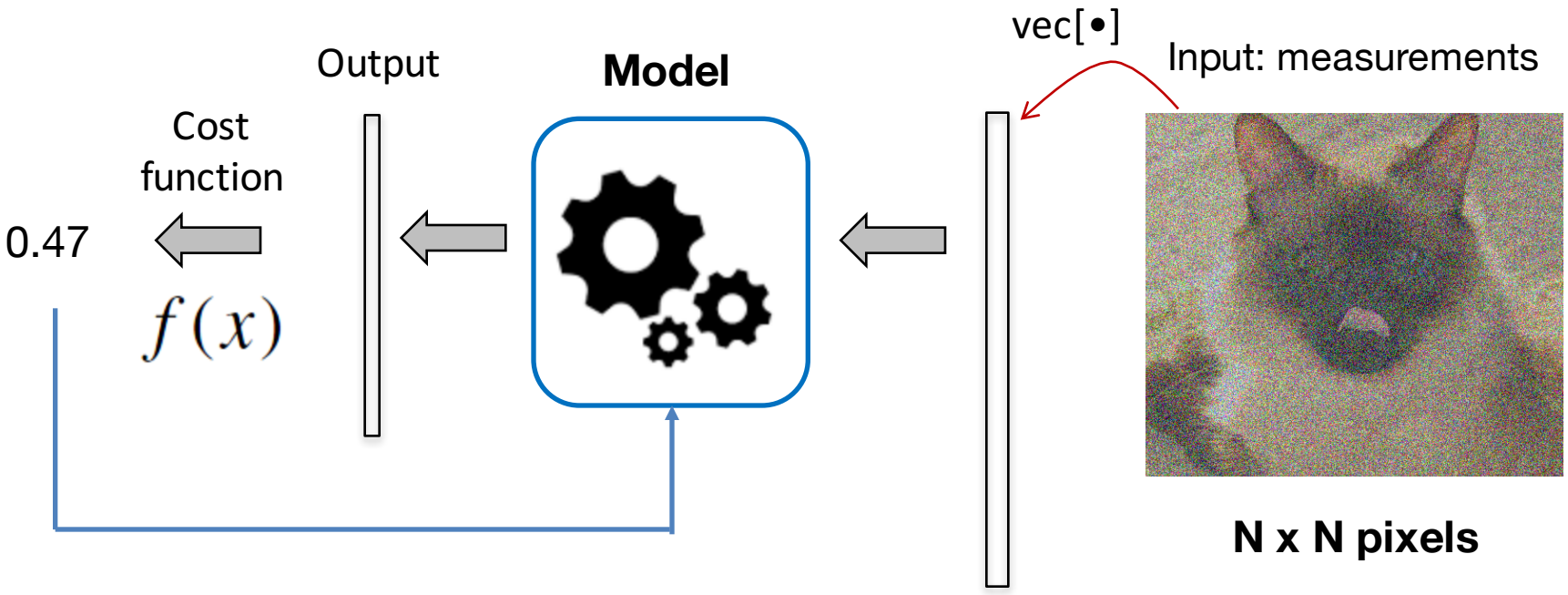
M

Input space dimension

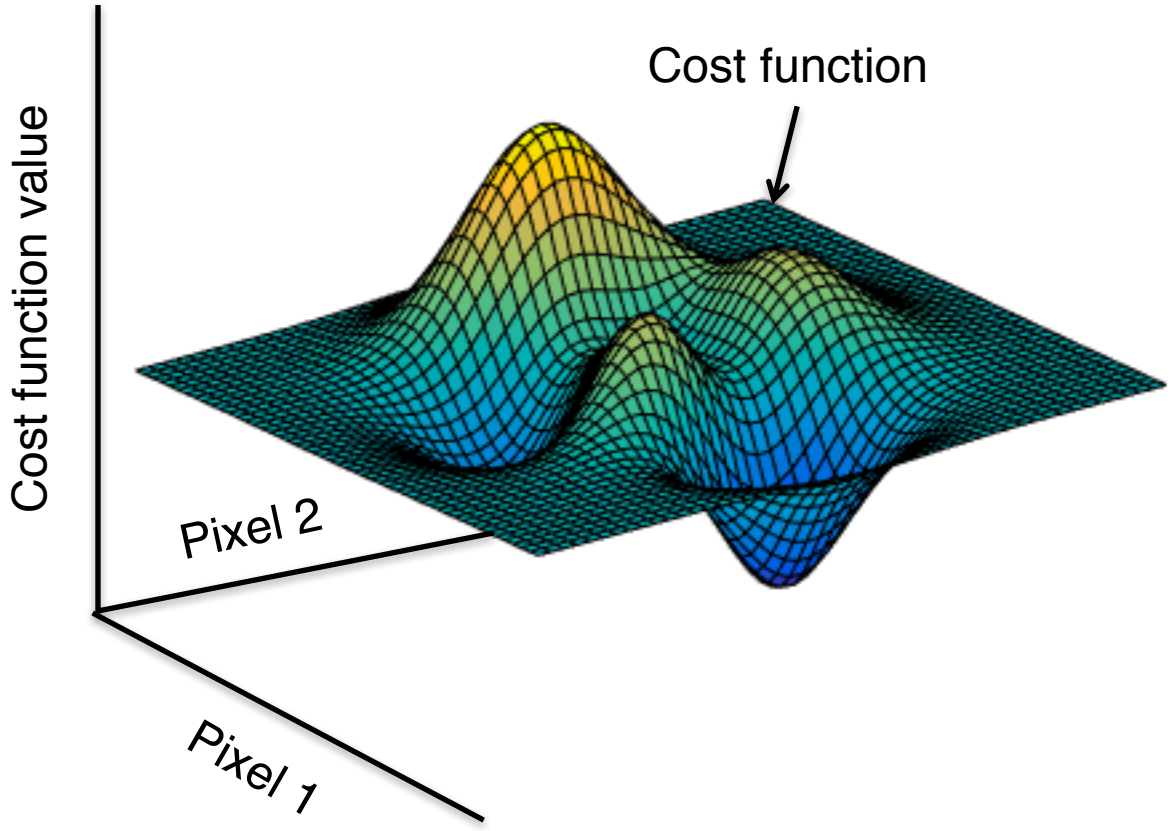
N^2

How well did we do?

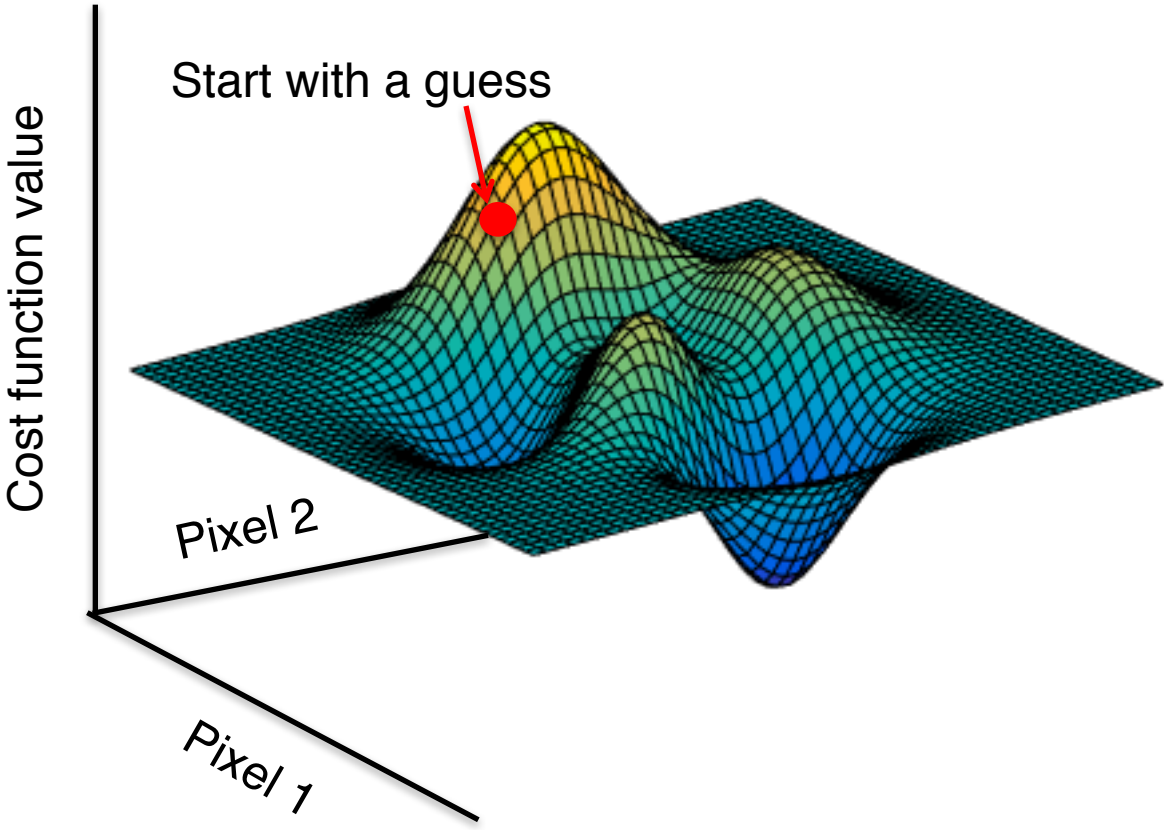
Machine learning: update model to decrease error



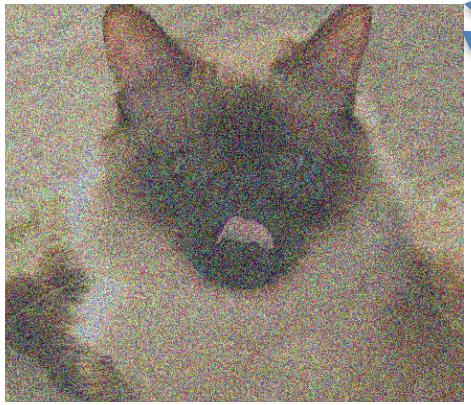
How well did we do?



De-noising: "What is the closest image to what I detected, except without so many fluctuations"?



Noisy image

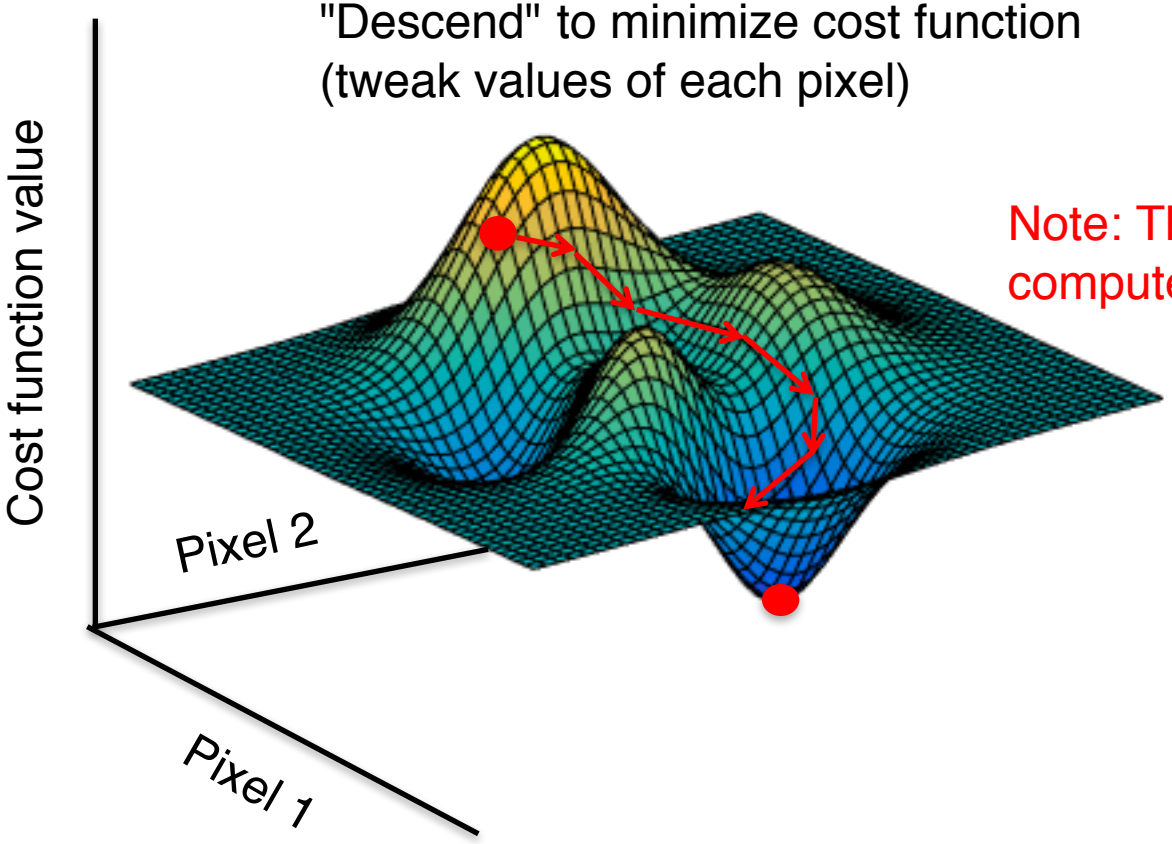


Pixel value 1

Pixel value 2

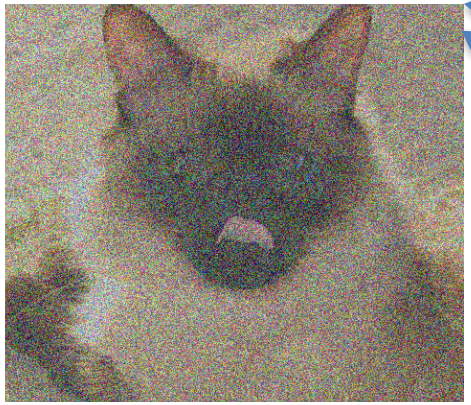
⋮

"Descend" to minimize cost function
(tweak values of each pixel)



Note: This math part computers are good at

Noisy image



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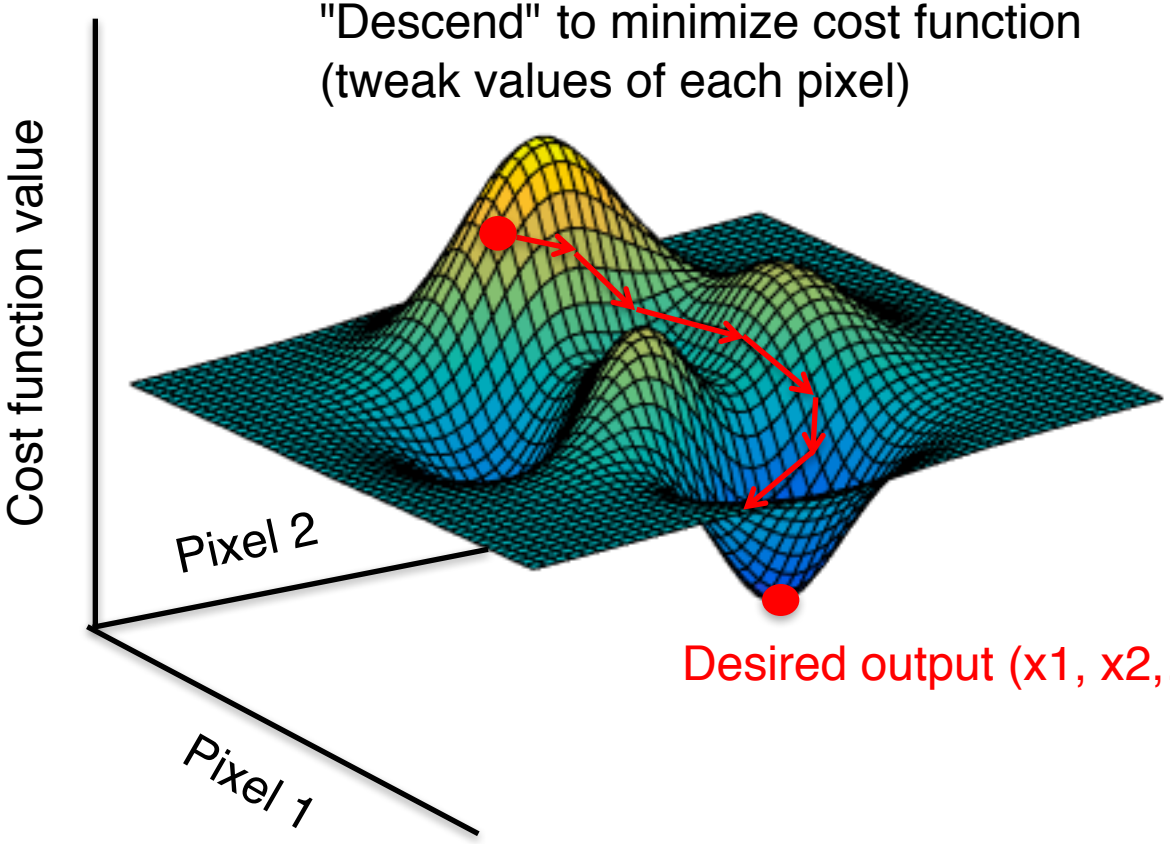
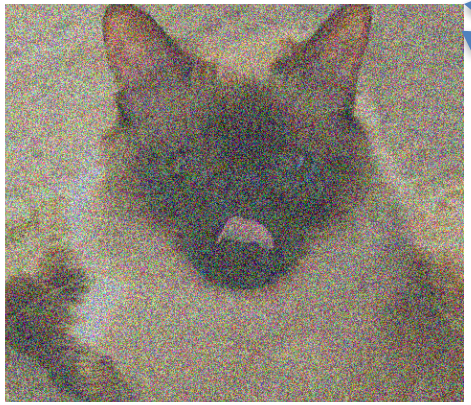


Desired output (x1, x2,…)

Noisy image

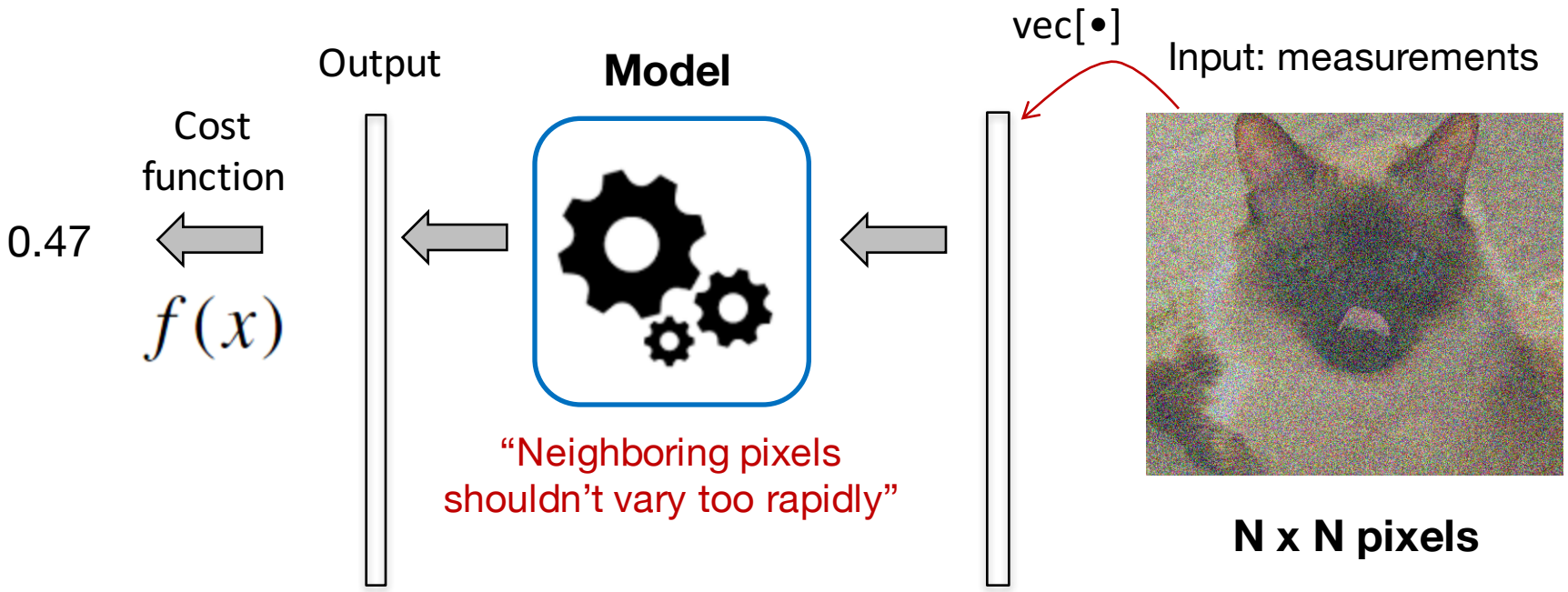


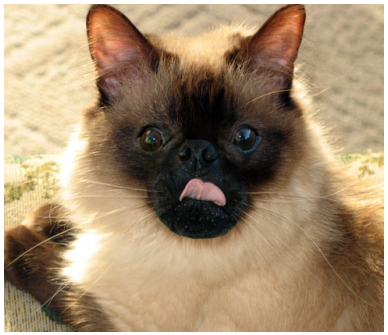
Pixel value 1
Pixel value 2
⋮

Desired output

x1
x2
⋮

Optimization pipeline for denoising





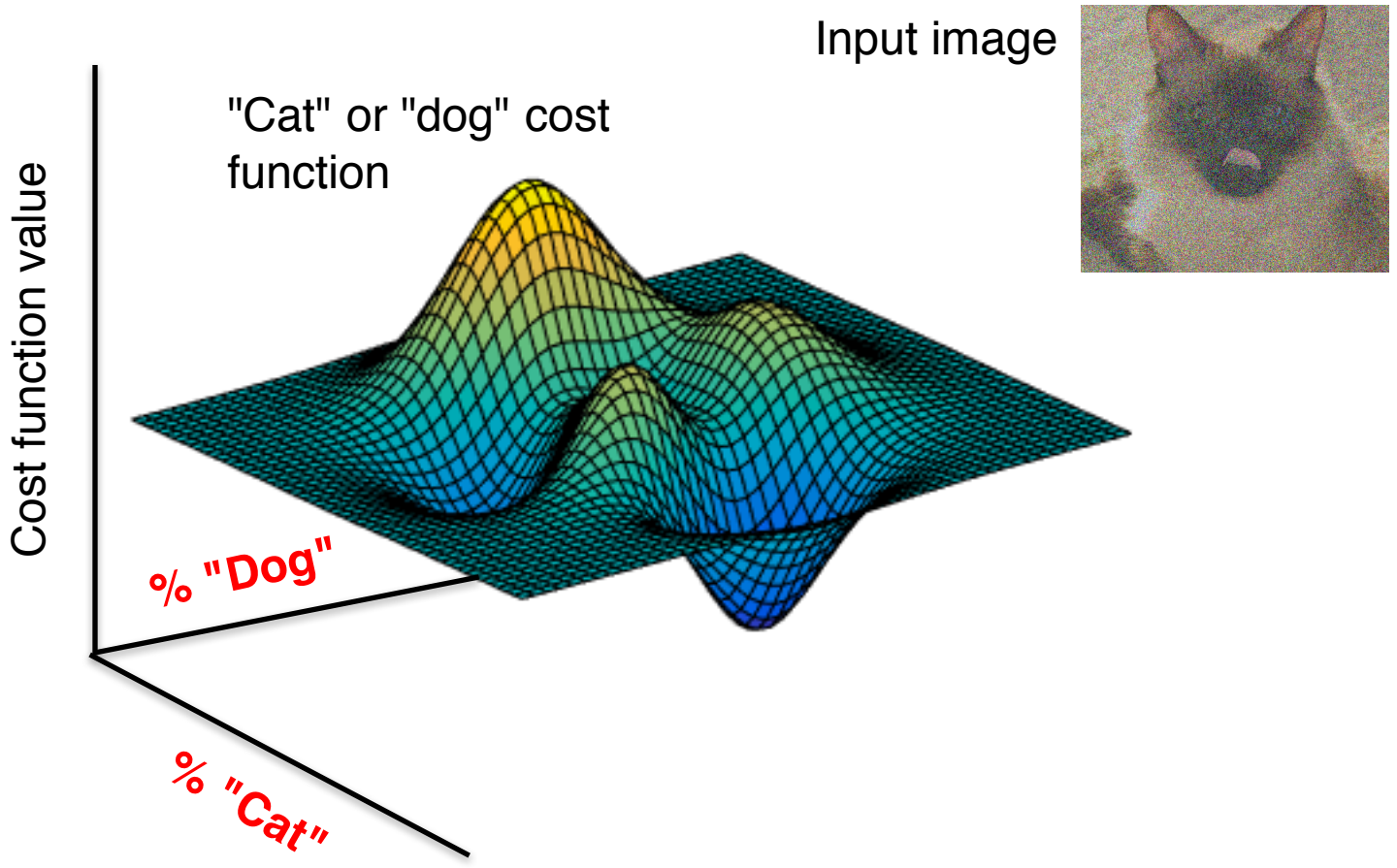
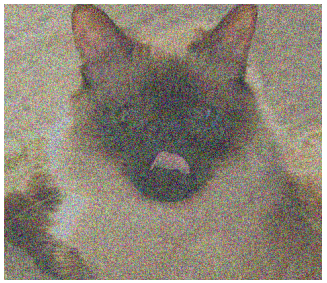
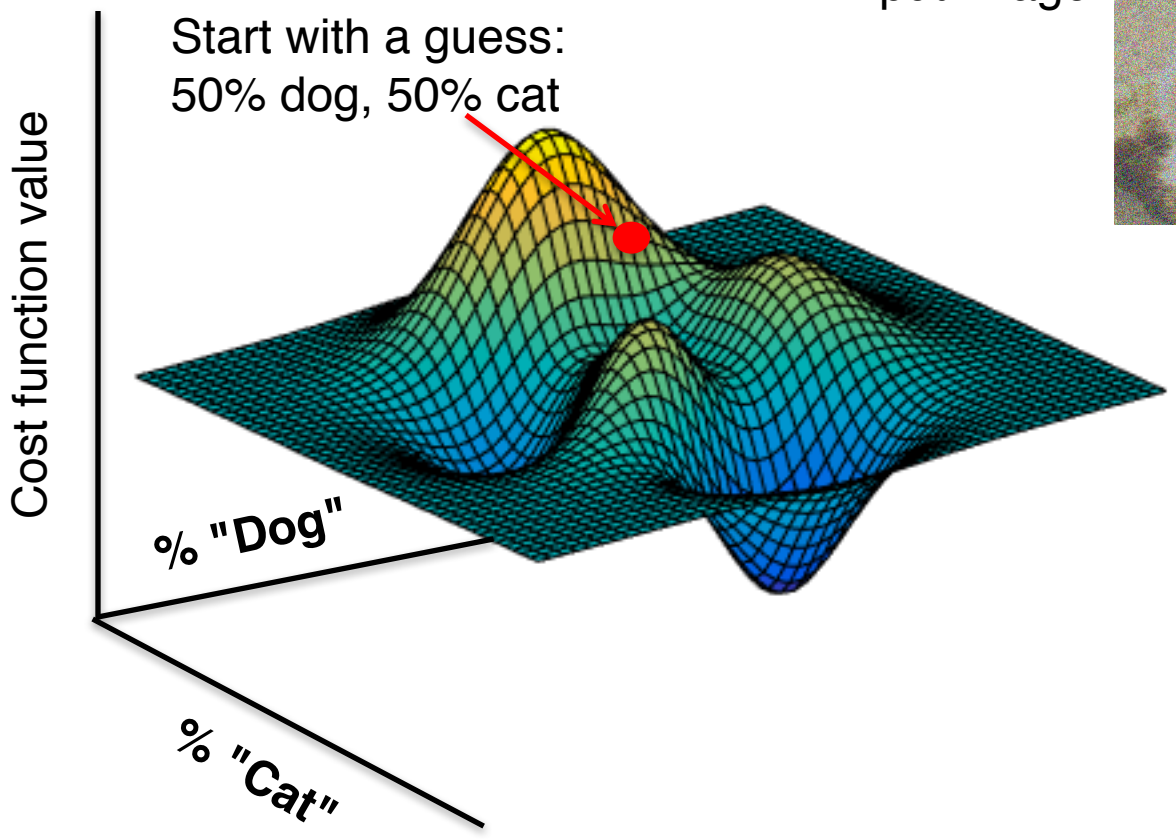


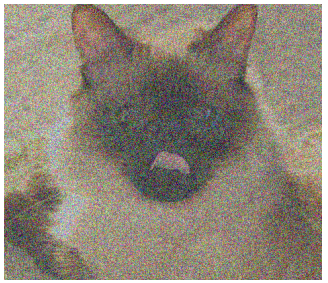
Image Classification: "Is the image of a dog or a cat"?

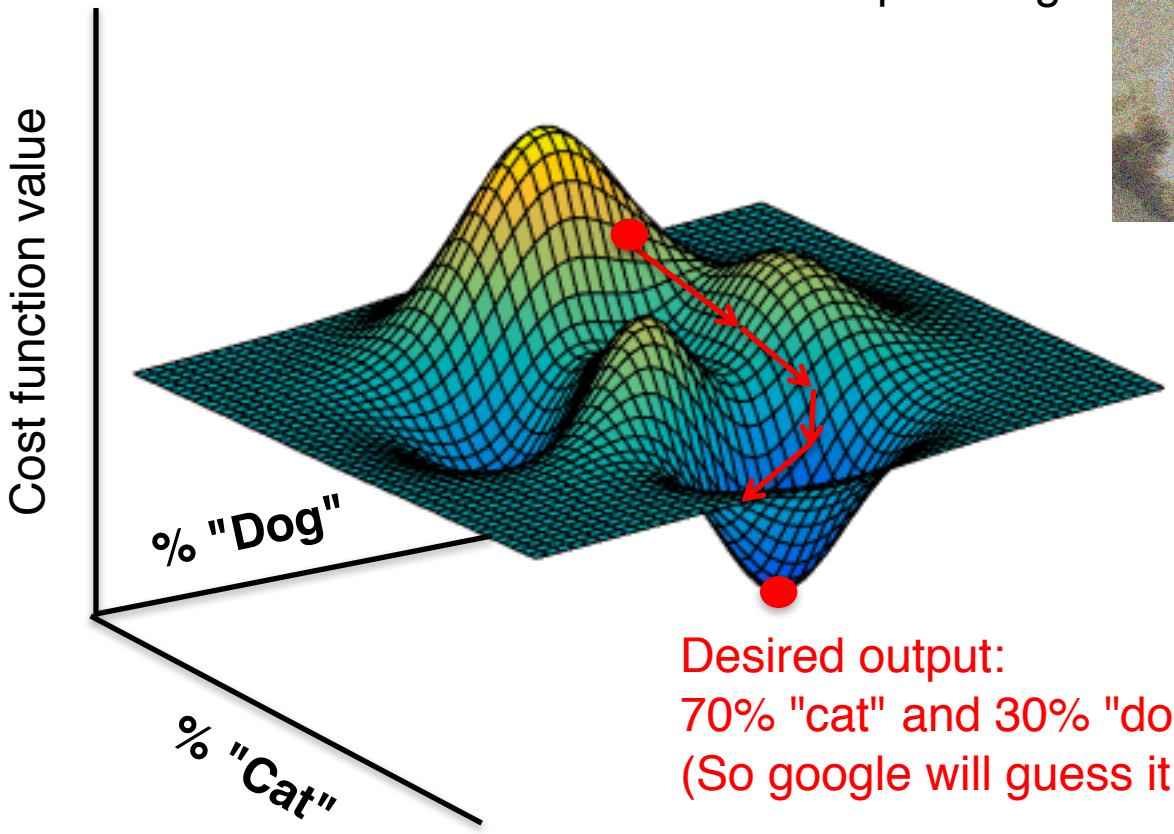
Input image





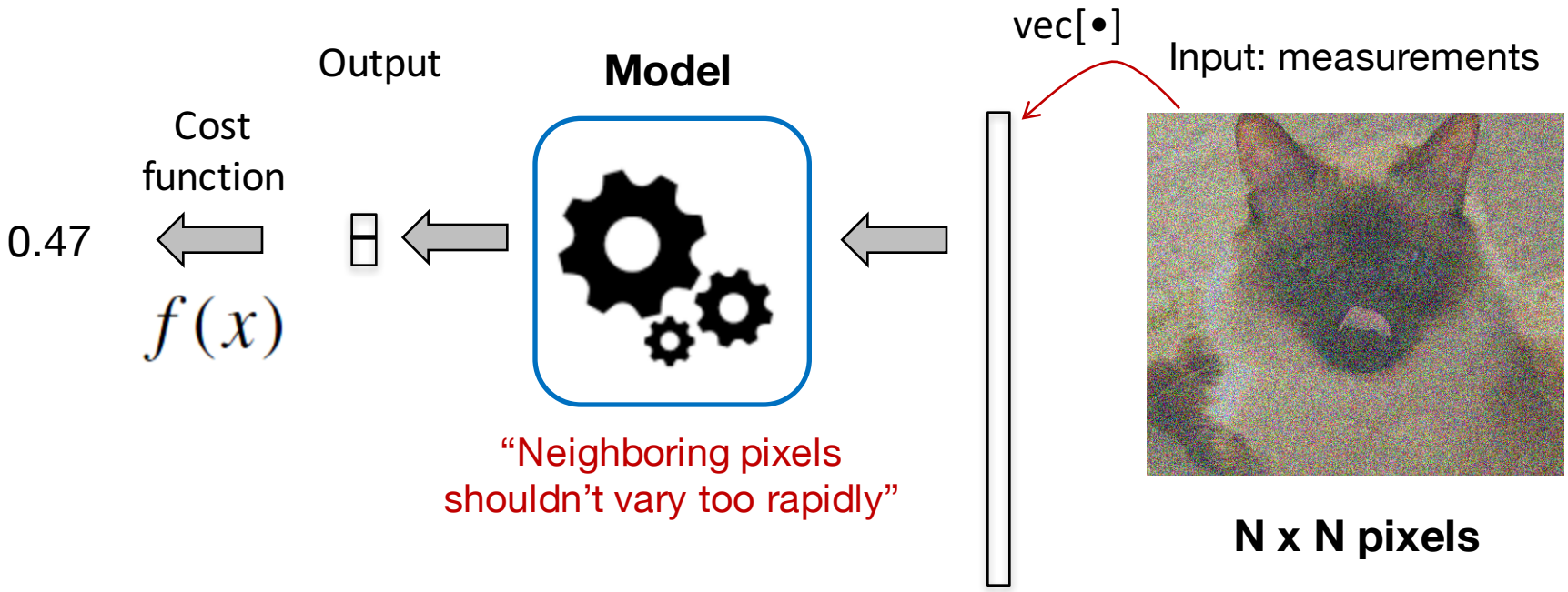
Input image





Desired output:
70% "cat" and 30% "dog"
(So google will guess it is likely a cat)

Optimization pipeline for classification



Performance measure

Mean-squared error

Output space dimension **2**

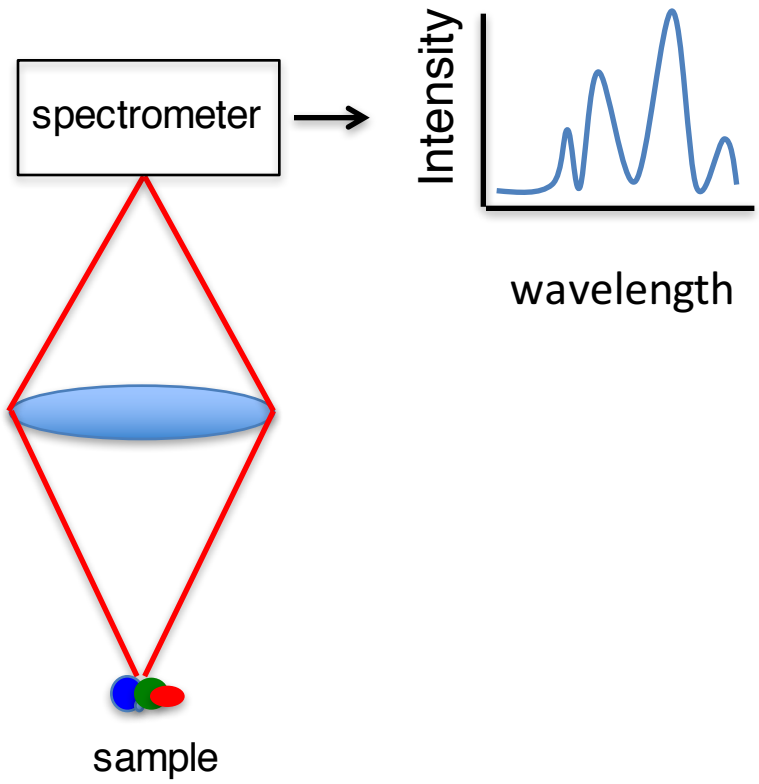
Input space dimension **N^2**

A simple example: spectral unmixing

(For whatever reason, whenever I get confused about optimization, I think about this example)

The setup:

- measure the color (spectral) response of a sample (e.g., how much red, green and blue there is, or several hundred measurements of its different colors).
- You know that the sample can only contain 9 different fluorophores.
- What % of each fluorophores is in your sample?



A simple example: spectral unmixing

3 elements of optimization:

1) Desired output

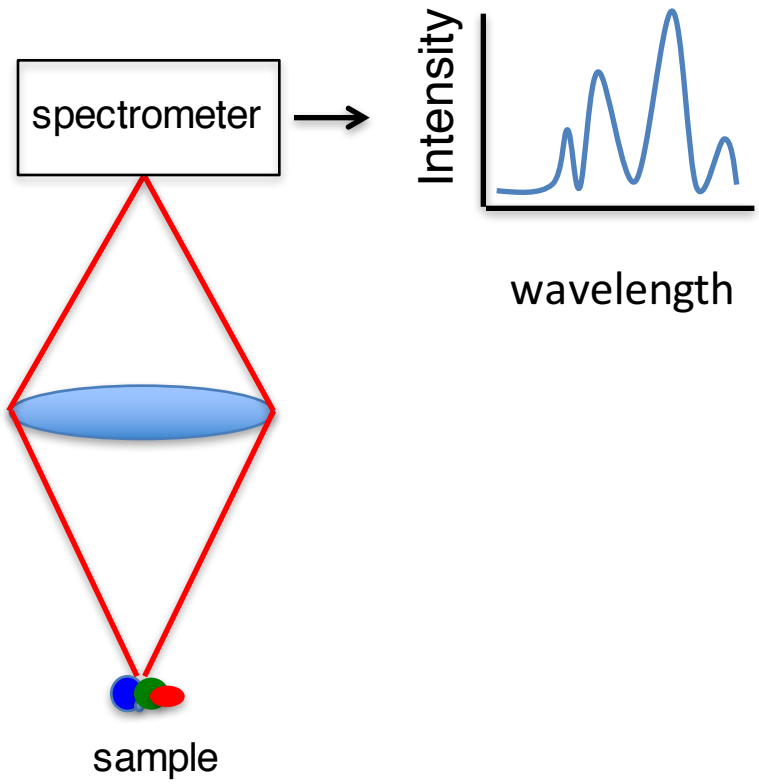
What % of each of the 9 fluorophores

2) The model

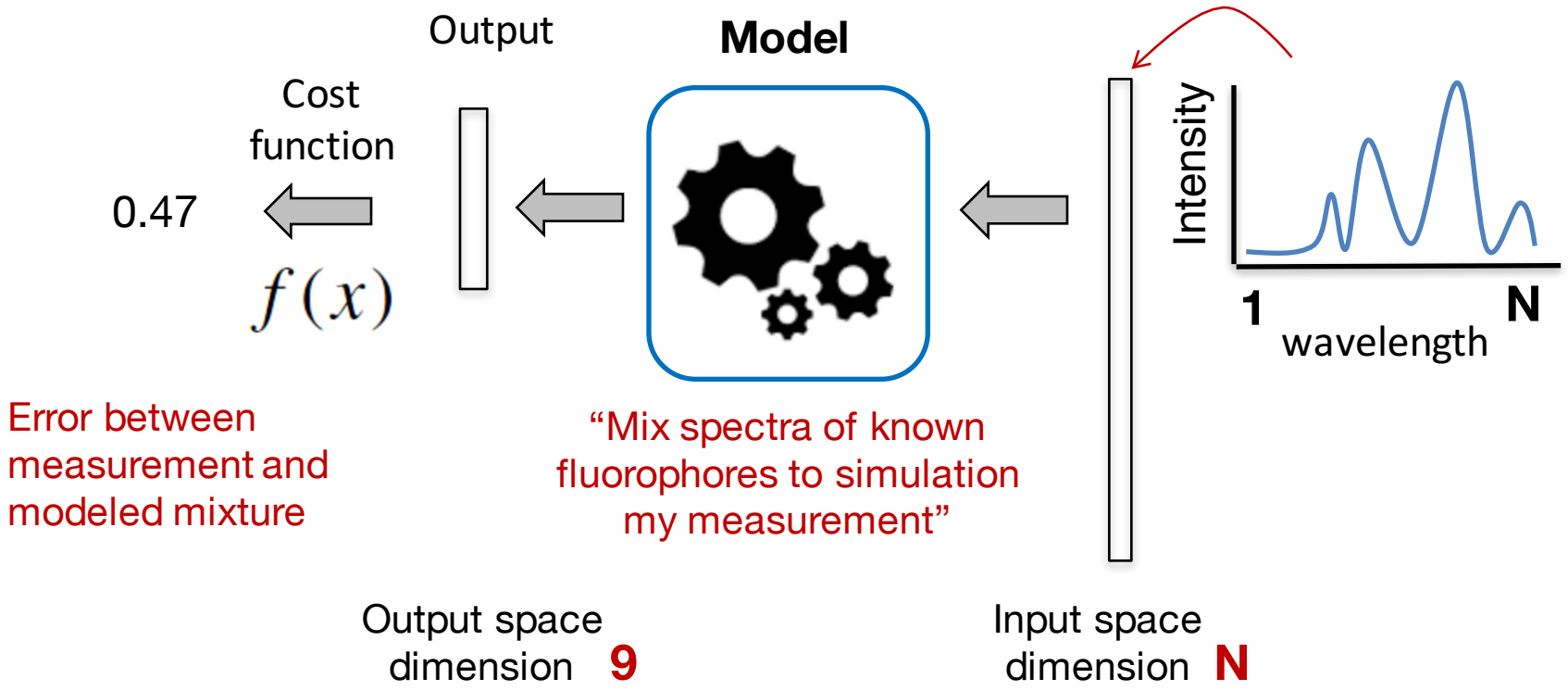
"Dictionary" of the 9 different spectra

3) The cost function

Minimum mean squared error (to start)

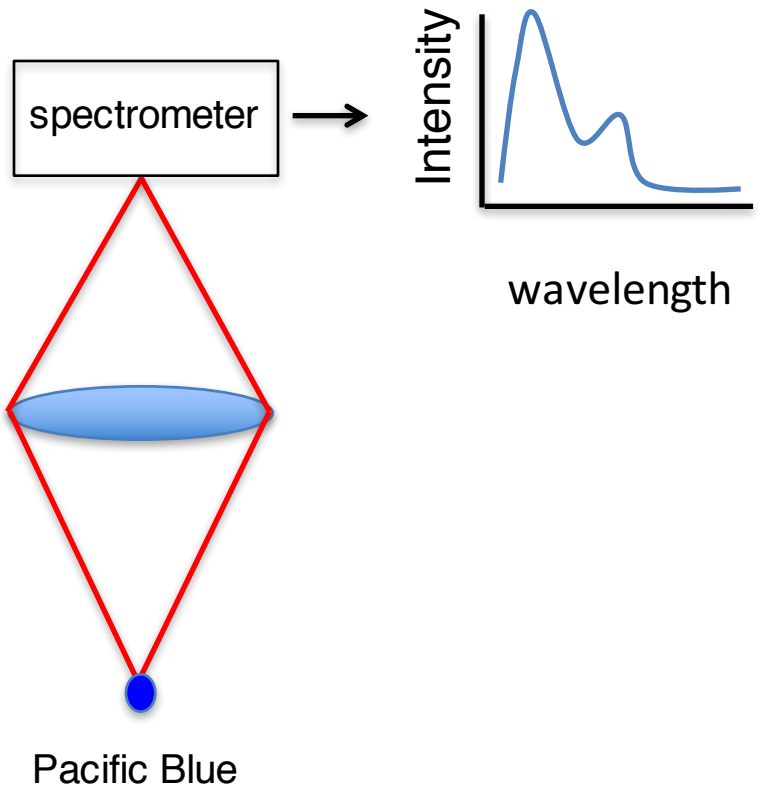


Optimization pipeline for spectral unmixing



Mathematical model for spectral unmixing

a) First make the "dictionary":



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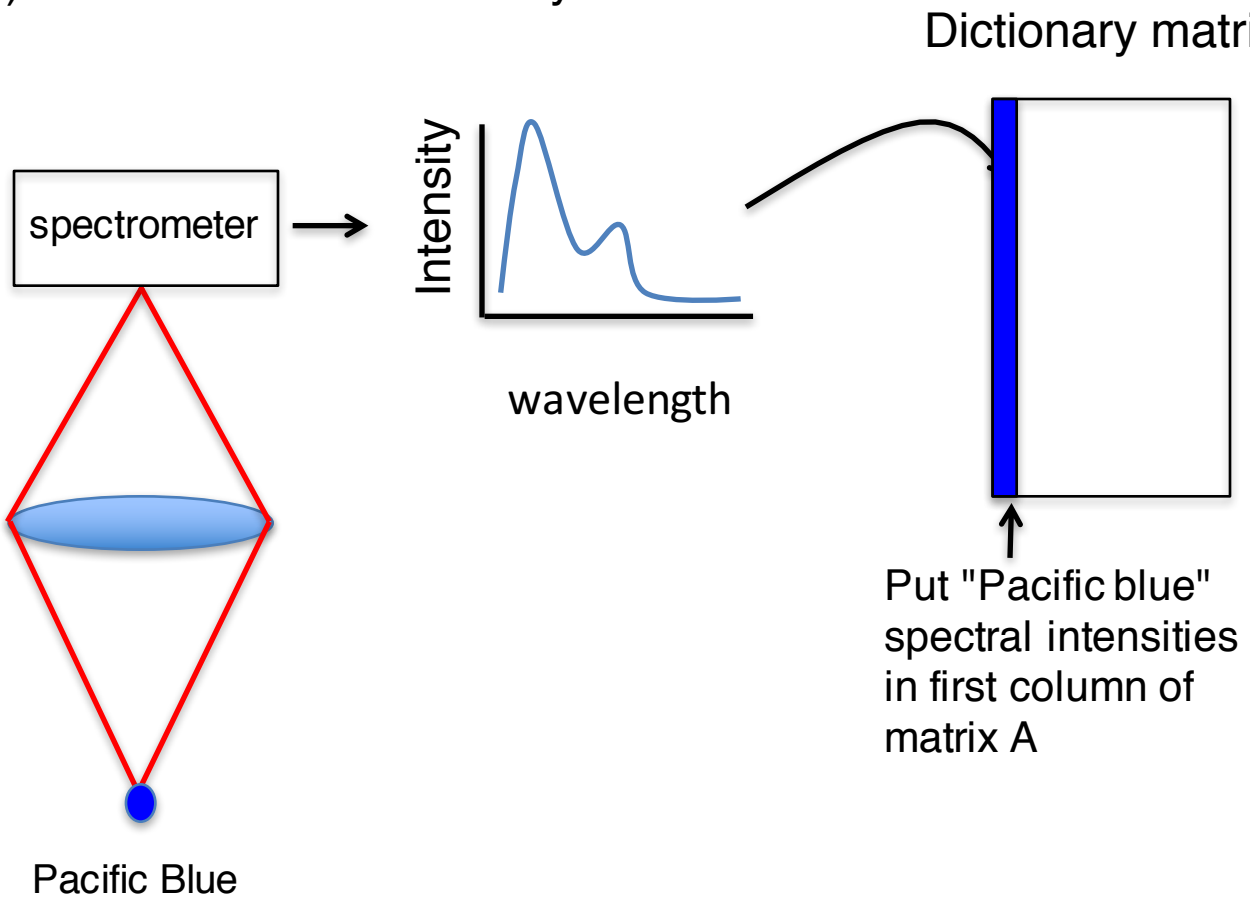

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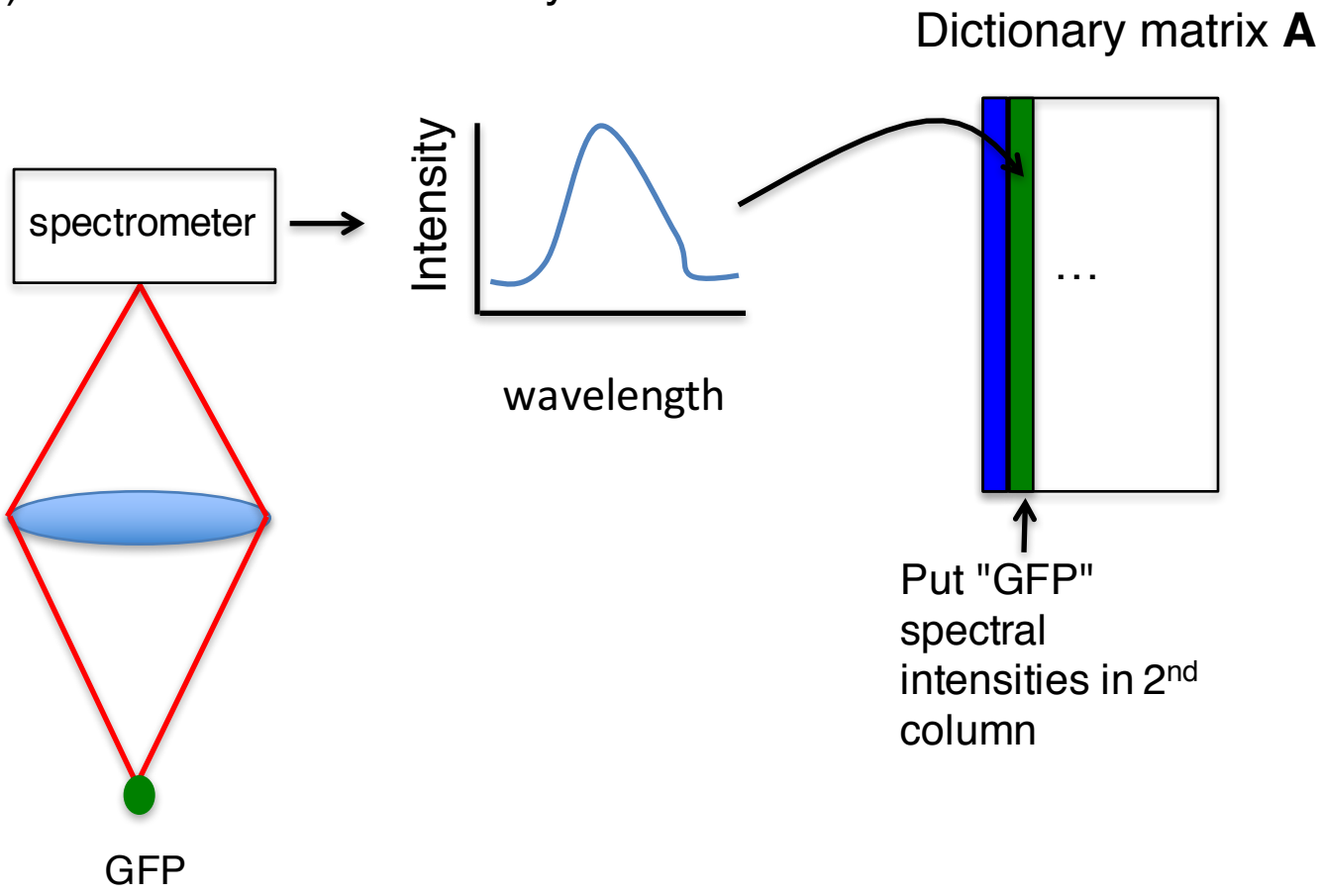
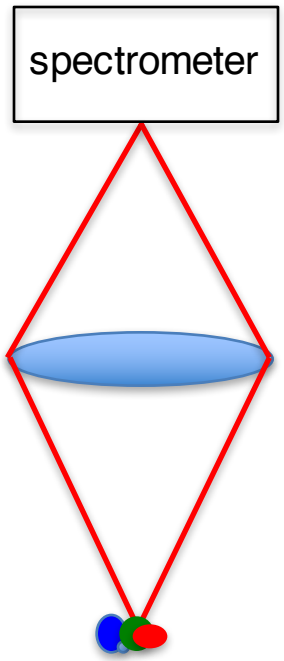


Mathematical model for spectral unmixing

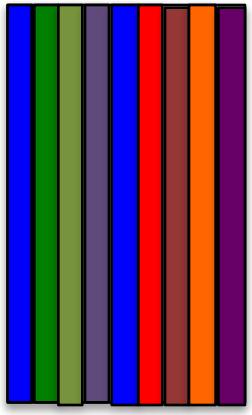
b) Model the unknown sample %'s

(the desired output)



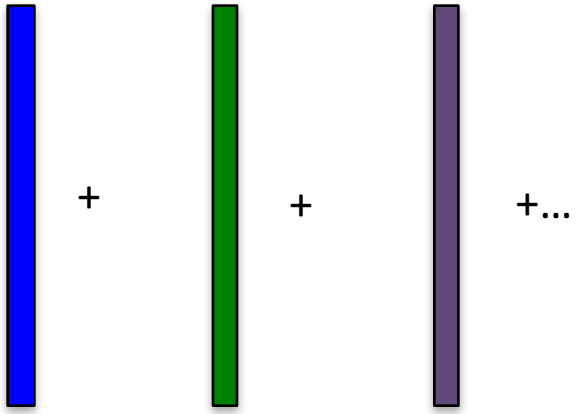
Unknown sample x

Dictionary matrix **A**



9 possible spectra

Some mixture…



Mathematical model for spectral unmixing

b) Model the unknown sample %'s

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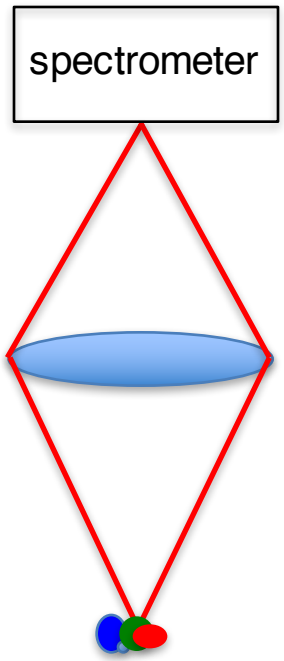

Unknown sample x

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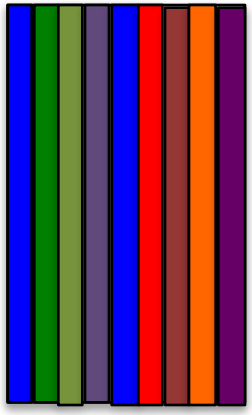
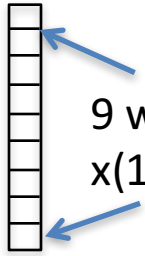
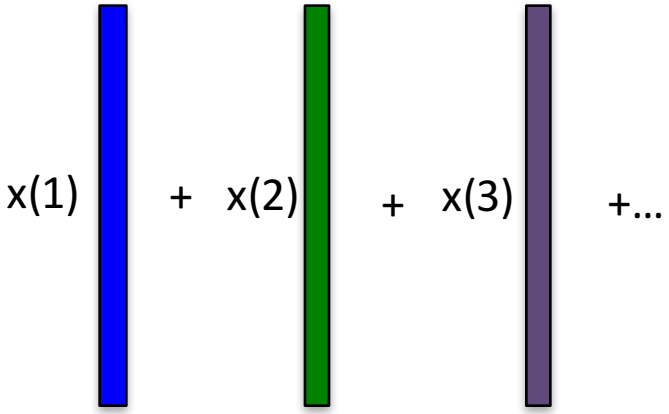


9 possible spectra

Unknown sample %'s **x**

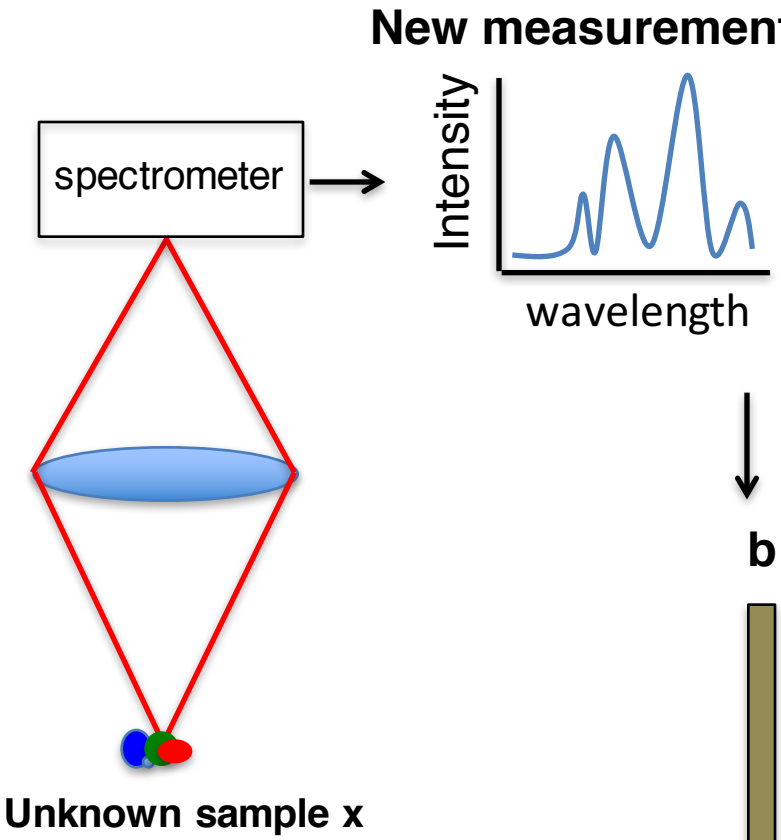


Each weight in x is percentage:

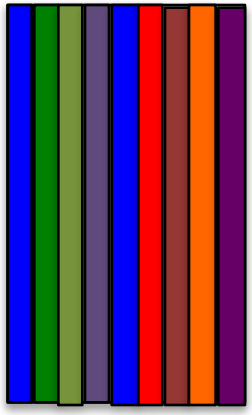


Mathematical model for spectral unmixing

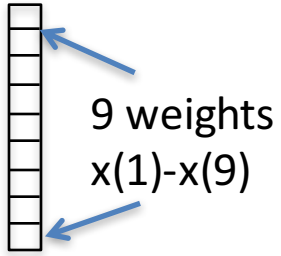
c) Model the known sample data

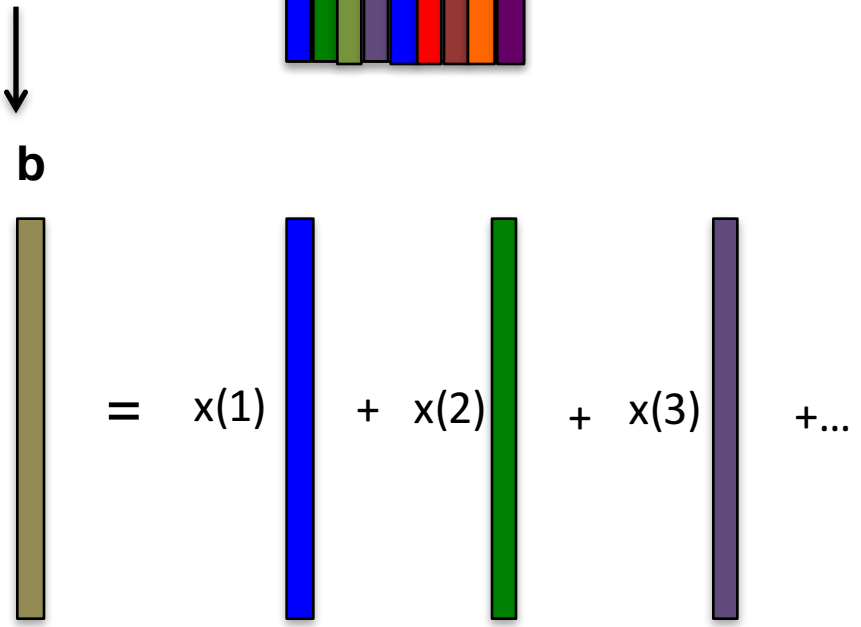


Dictionary matrix **A**

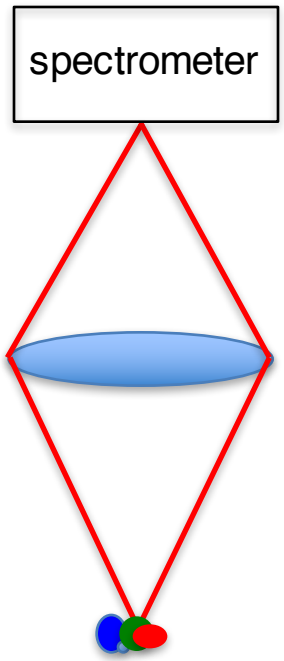


Unknown sample %'s **x**

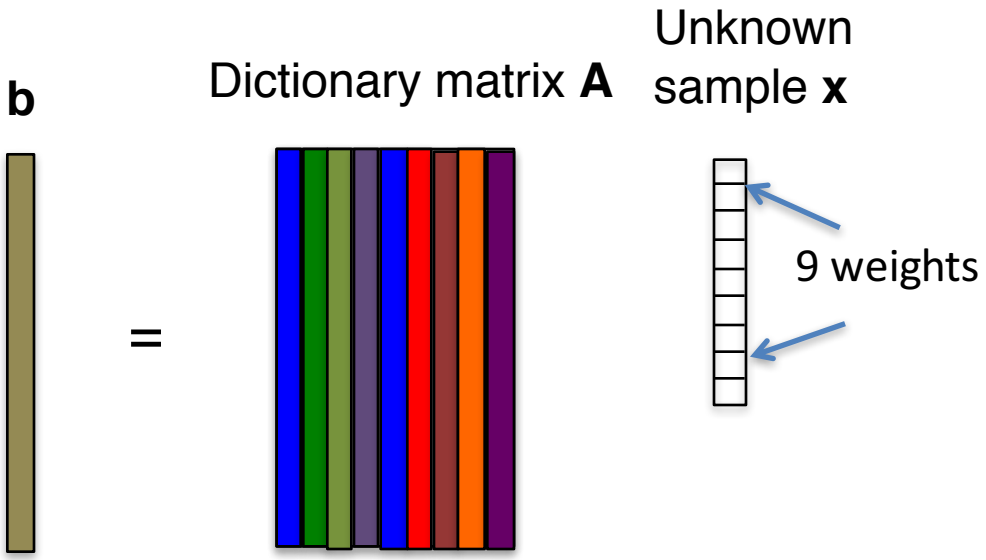




Mathematical model for spectral unmixing



Unknown sample x

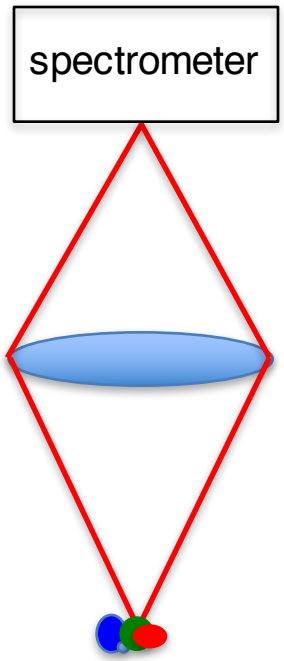


Matrix equation: **b=Ax**

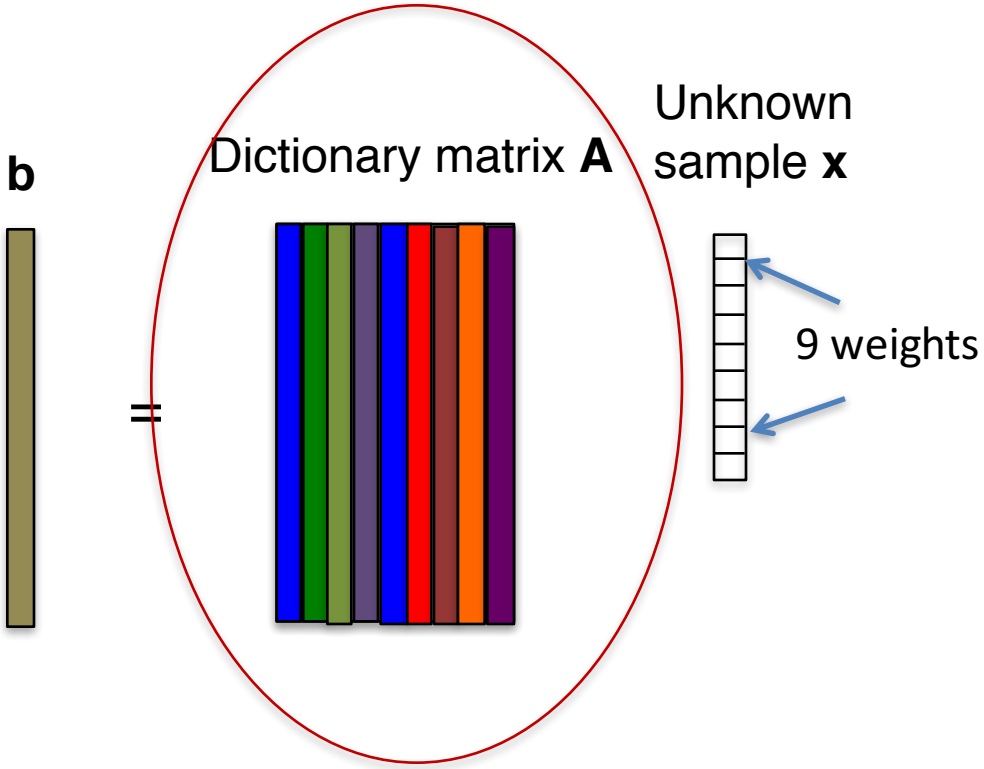
This is your model!

Goal: Given A and b, find x

Mathematical model for spectral unmixing



Unknown sample x



Data in A can be thought of , in some sense, as "training data"

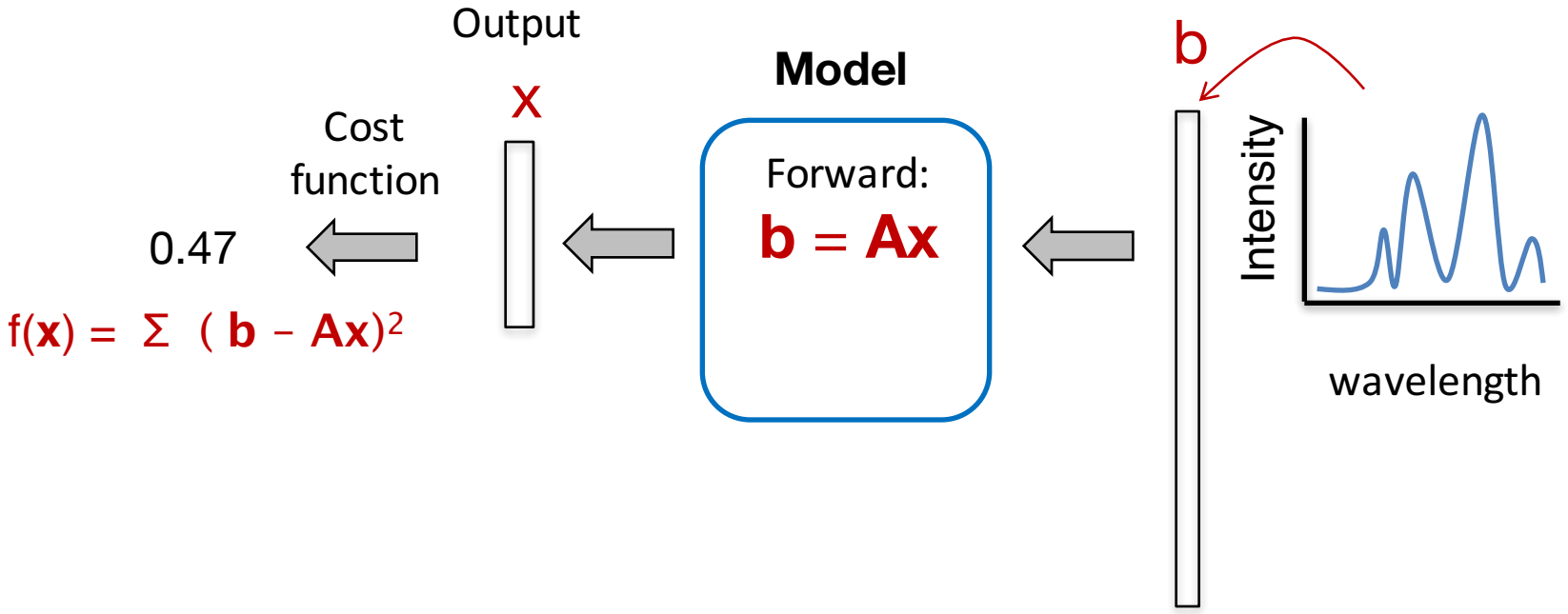
Cost function for spectral unmixing

b = **Ax** won't always be true, due to noise (actually, **b** = **Ax**+**n**)

Common cost function is minimum mean-squared error:

$$\text{Cost function } f(\mathbf{x}) = \sum_{\text{spectral measurements}} (\mathbf{b} - \mathbf{Ax})^2$$

Optimization pipeline for denoising



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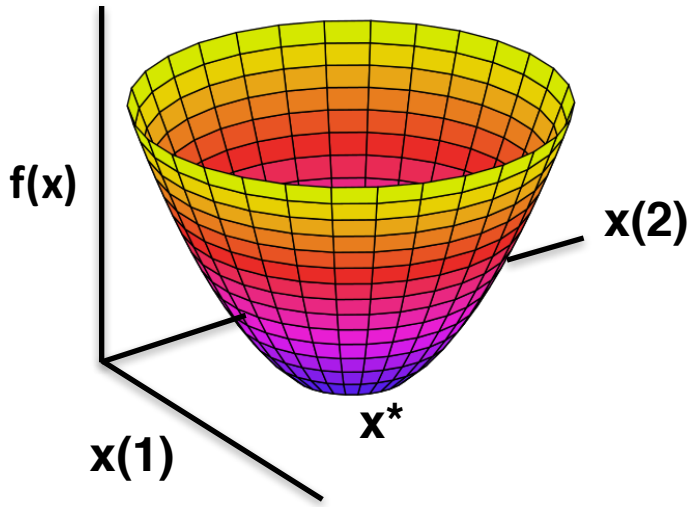
Find mixture **x** of known spectra **A** that is as close as possible to measurement **b**

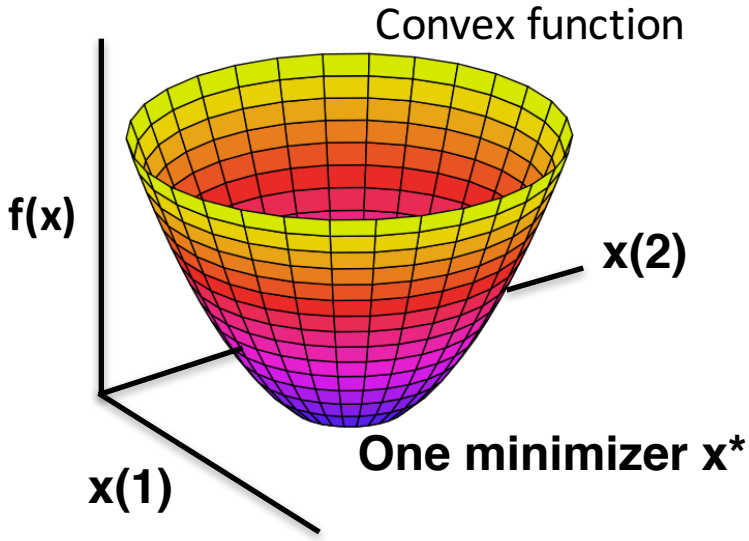
$$\mathbf{x}^* = \text{minimize } f(\mathbf{x})$$



Cost function for spectral unmixing

$$f(\mathbf{x}) = \sum (\mathbf{b} - \mathbf{A}\mathbf{x})^2$$

spectral measurements

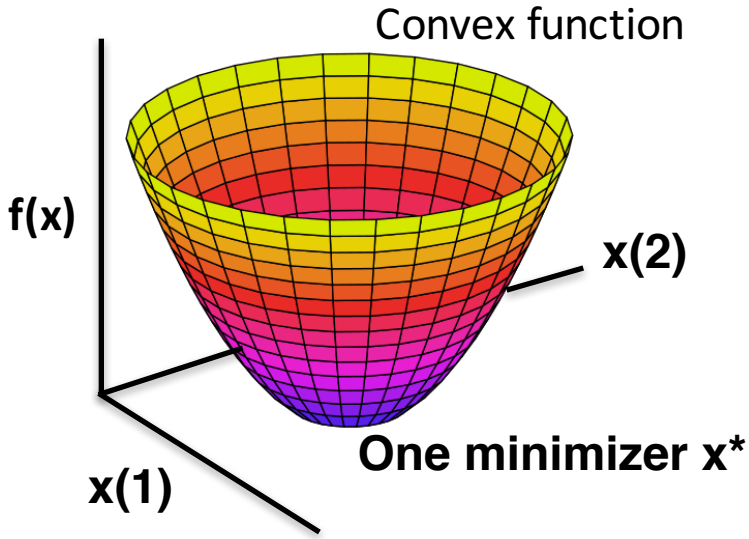


f(**x**) is convex, so finding **x*** is easy via its gradient:

Cost function for spectral unmixing

$$f(\mathbf{x}) = \sum (\mathbf{b} - \mathbf{A}\mathbf{x})^2$$

spectral measurements



f(**x**) is convex, so finding **x*** is easy via its gradient:

$$d/d\mathbf{x}\, f(\mathbf{x}) = d/d\mathbf{x} \sum (\mathbf{b} - \mathbf{A}\mathbf{x})^2 = 0$$

$$df/d\mathbf{x} = \Sigma\, d/d\mathbf{x} (\mathbf{b} - \mathbf{A}\mathbf{x})^2$$

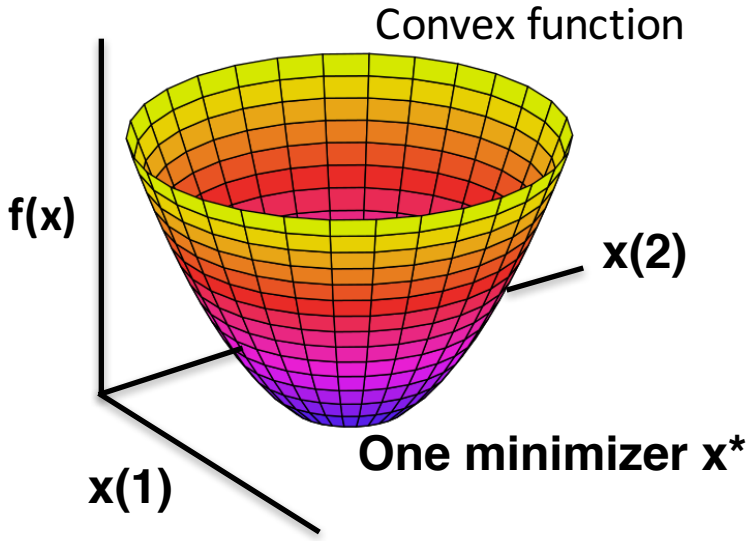
$$df/dx[j] = \Sigma\, 2 (\mathbf{b} - \mathbf{A}\mathbf{x}) .* \mathbf{a}(:,j)$$

$$df/d\mathbf{x} = \mathbf{A}^T(\mathbf{b} - \mathbf{A}\mathbf{x}^*)$$

Cost function for spectral unmixing

$$f(\mathbf{x}) = \Sigma \ (\mathbf{b} - \mathbf{A}\mathbf{x})^2$$

spectral measurements



Method 1: *Gradient descent* – follow gradient downhill to solution **x***

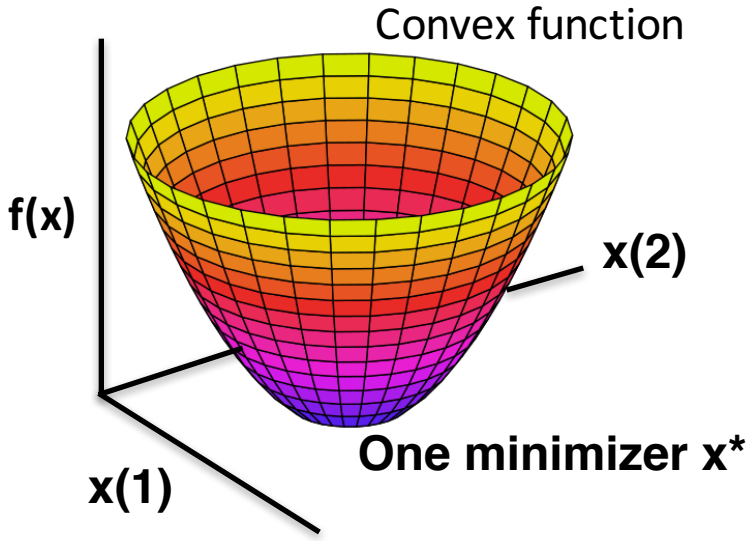
Algorithm 4.1 An algorithm to minimize $f(\boldsymbol{x}) = \frac{1}{2}||\boldsymbol{A}\boldsymbol{x} - \boldsymbol{b}||_2^2$ with respect to $\boldsymbol{x}$ using gradient descent, starting from an arbitrary value of $\boldsymbol{x}$.

Set the step size (ϵ) and tolerance (δ) to small, positive numbers.
while $||\boldsymbol{A}^\top \boldsymbol{A}\boldsymbol{x} - \boldsymbol{A}^\top \boldsymbol{b}||_2 > \delta$ **do**
  $\boldsymbol{x} \leftarrow \boldsymbol{x} - \epsilon \left(\boldsymbol{A}^\top \boldsymbol{A}\boldsymbol{x} - \boldsymbol{A}^\top \boldsymbol{b}\right)$
end while

Cost function for spectral unmixing

$$f(\mathbf{x}) = \sum (\mathbf{b} - \mathbf{A}\mathbf{x})^2$$

spectral measurements



Method 2: *Direct solution* – set derivative to 0 to find **x*** directly

$$df/d\mathbf{x} = \mathbf{A}^T(\mathbf{b} - \mathbf{A}\mathbf{x}^*) = 0$$ ← x* is where gradient of f(x) is zero

$$\mathbf{A}^T\mathbf{b} = \mathbf{A}^T\mathbf{A}\mathbf{x}^* \longrightarrow$$

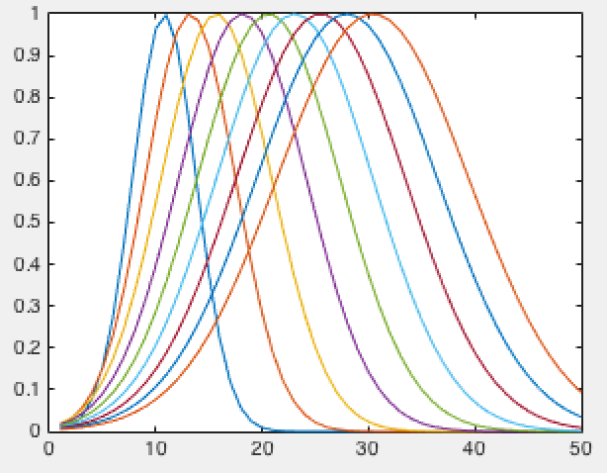
$$\boxed{(\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{b} = \mathbf{x}^*}$$ "Moore-Penrose Pseudo-inverse"

(Note: setting gradient to 0 and solving is usually hard to do…)

Example unmixing with the pseudo-inverse

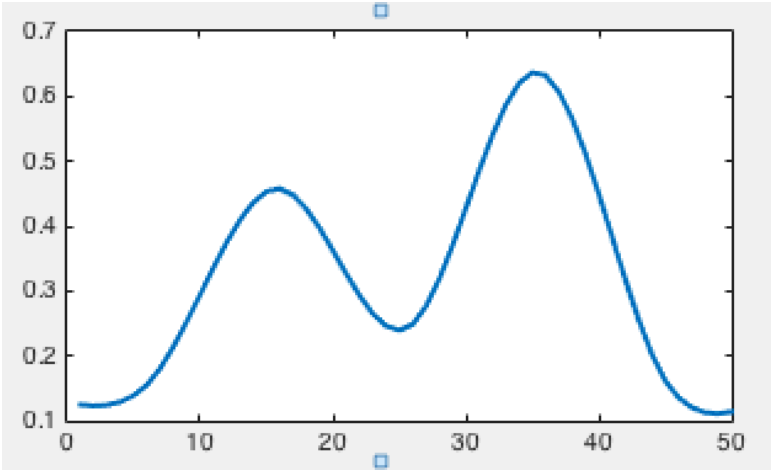
Moore-Penrose Pseudo-inverse: $\mathbf{x^* = (A^T A)^{-1} A^T b}$

Example dictionary A
9 spectra



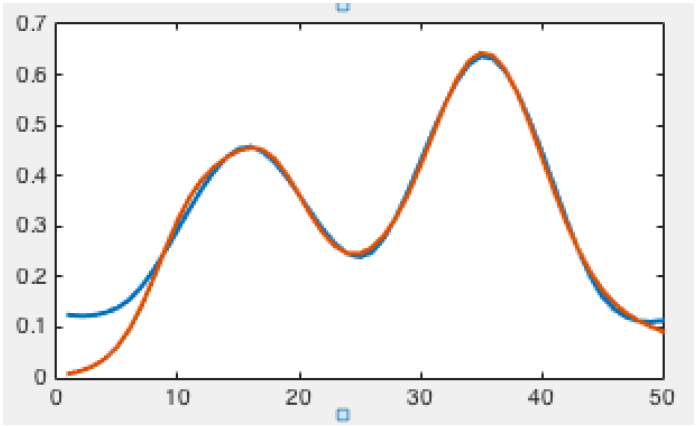
Example x, compute Ax

Example detected spectra b



Compute pseudo-inverse, b*=Ax* is red curve:

Good fit!



PROBLEM:

x* = [0.2, -1.1, -1.6, …]

Solution has negative weights!

Not physically possible…

Example unmixing with the pseudo-inverse

Moore-Penrose Pseudo-inverse: $\mathbf{x}^* = (\mathbf{A}^T\mathbf{A})^{-1}\,\mathbf{A}^T\,\mathbf{b}$

```
n = 50; %number of pixels
m = 9; %number of spectral
A=zeros(n,m); %known dictionary of spectra
for j=1:m
    A(:,j) = exp(-(linspace(-1,1,n)+.5-.1*j+.2).^2/(.03*j));
end
%Simulate some spectra
b = imresize(rand([5,1]),[n 1]);
x_opt = A\b;
%Show results
figure;plot(b); hold all; plot(A*x_opt);
```

Pseudo-inverse = one line

Spectral un-mixing with a positivity constraint

Option 1: Add a constraint

Minimize $f(\mathbf{x}) = \Sigma \ (\mathbf{b} - \mathbf{A}\mathbf{x})^2$ Convex cost function

Subject to $\mathbf{x} >= 0$ Convex constraint

*When you have constraints, can use **CVX**, convex toolbox for Matlab

http://cvxr.com/cvx/

Spectral un-mixing with a positivity constraint

Option 1: Add a constraint

```
%%%%%%%%%%%%%
addpath '/users/Roarke/Documents/Matlab/cvx'; cvx_setup;
cvx_begin
    variable xc(m);
    minimize( norm(A*xc-b) );
    subject to
        xc >= 0;
cvx_end
%Show results
figure;plot(b); hold all; plot(A*xc);
%%%%%%%%%%%%%
```

Spectral un-mixing with a positivity constraint

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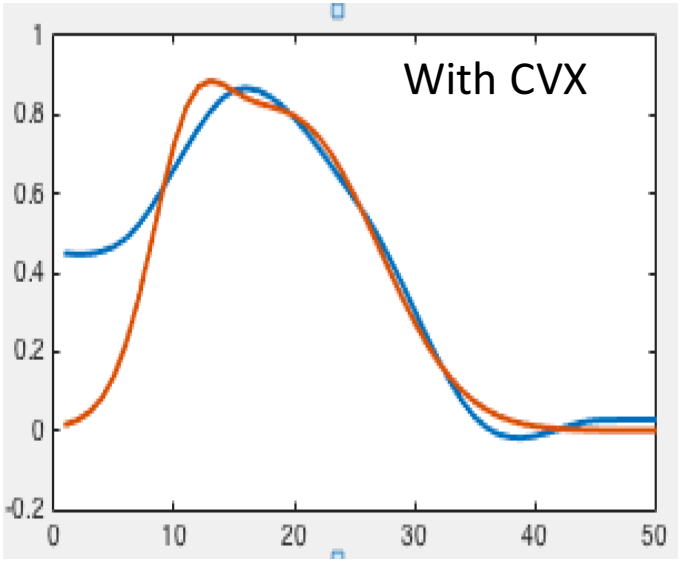

x*

0.3612
0.2238
0.0006
0.0000
0.7336
0.0000
0.0000
0.0000
0.0000

Spectral un-mixing with a positivity constraint

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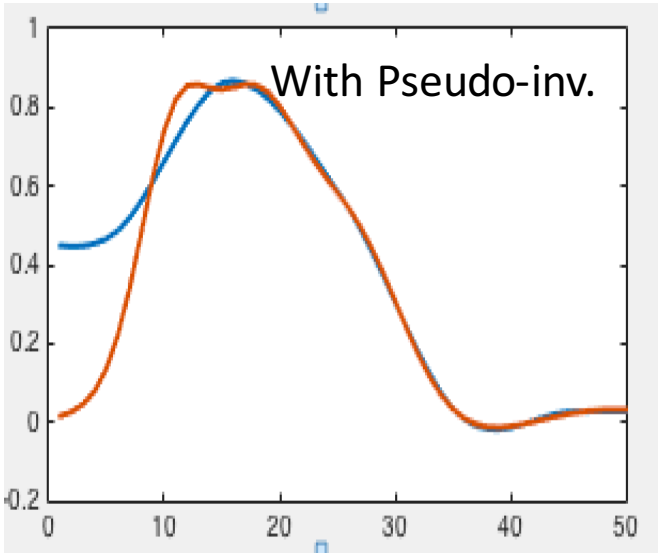
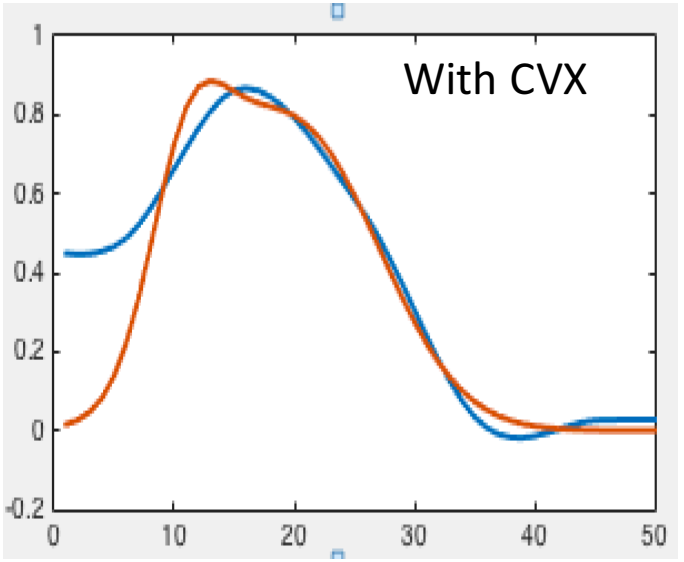
x*

0.6683
-1.5880
5.7848
-11.7459
17.9304
-20.1231
18.3572
-10.7984
2.8557





x*

0.3612
0.2238
0.0006
0.0000
0.7336
0.0000
0.0000
0.0000
0.0000

Spectral un-mixing with a positivity constraint

Option 2: Modify cost function

Minimize $f(\mathbf{y}) = \Sigma \ (\mathbf{b} - \mathbf{A}\mathbf{y}^2)^2$

$\mathbf{y}^2 = \mathbf{x}$ is dummy variable, will change cost function and gradient

*When you don't have constraints but can find the gradient, use **Minfunc**

https://www.cs.ubc.ca/~schmidtm/Software/minFunc.html

Spectral un-mixing with a positivity constraint

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```
%%%%%%%%%%%%
%3. Minfunc
addpath '/users/Roarke/Documents/Matlab/minFunc_2012';
startVec = ones(m,1);
spectrum_anonymous = @(startVec)spectrum(startVec, b, A);
%Evaluate with minfunc
[xm, msevalue, moreinfo] = minFunc(@(startVec)spectrum_anonymous(startVec), startVec, options);
figure;plot(b); hold all; plot(A*abs(xm).^2);
```

Spectral un-mixing with a positivity constraint

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figure;plot(b); hold all; plot(A*abs(xm).^2);
```

```
function [err_function, grad_function] = spectrum(input_vec, b, A)

%for direct pseudo-inverse - no constraints or dummy
 %err_function = norm(A*input_vec - b);
 %grad_function = A'*(A*input_vec - b);

 err_function = norm(A*abs(input_vec).^2 - b);
 grad_function = A'*((A*abs(input_vec).^2 - b) .* conj(A*input_vec));
```

Spectral un-mixing with a positivity constraint

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Minimize $f(\mathbf{y}) = \Sigma \ (\mathbf{b} - \mathbf{A}\mathbf{y}^2)^2$

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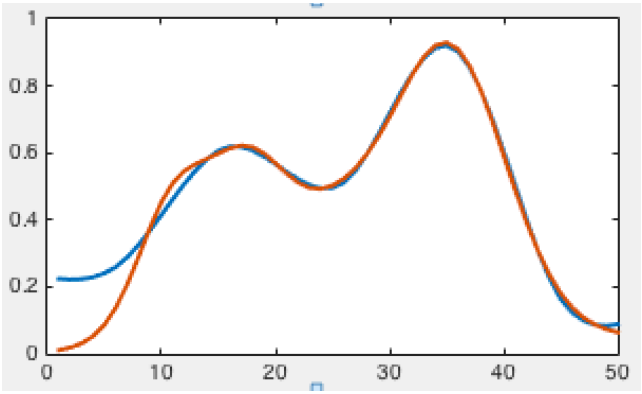
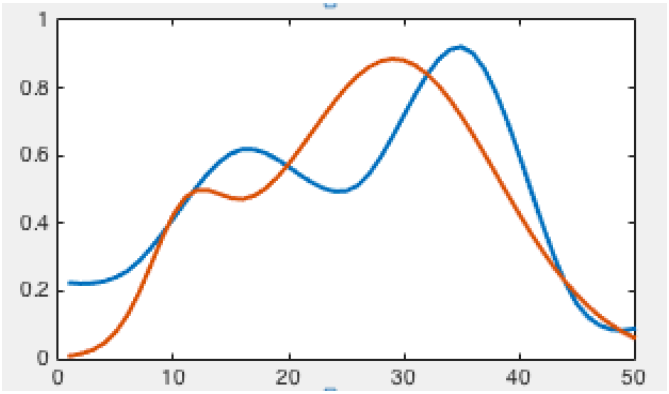
Pseudo-inverse



Dummy variable w/ minfunc



x*

0.5013
0.3345
0.1811
0.0367
0.0132
0.0705
0.2626
0.5080
0.7539

Not working too well, gradient could be wrong?

Other bells and whistles

1) Sometimes see solutions where x values get really big

Fix this with a "*regularizer*":

$$\text{Minimize } f(\mathbf{x}) = \Sigma\ (\ \mathbf{b} - \mathbf{Ax})^2 + C^*\Sigma\ (x)^2$$

"Don't let x vary too much"

Choose constant C appropriately

2) If you think your signal is "sparse", then it probably has mostly zeros. Can include this in your model with an "L1" cost function:

$$\text{Minimize } f(\mathbf{x}) = \Sigma\ |\ \mathbf{b} - \mathbf{Ax}\ |$$

- An extremely simple modification with pretty strong implications