

Title: PSI 2019/2020 - Computational Physics - Lecture 14

Speakers: Erik Schnetter

Collection: PSI 2019/2020 - Computational Physics

Date: March 09, 2020 - 1:30 PM

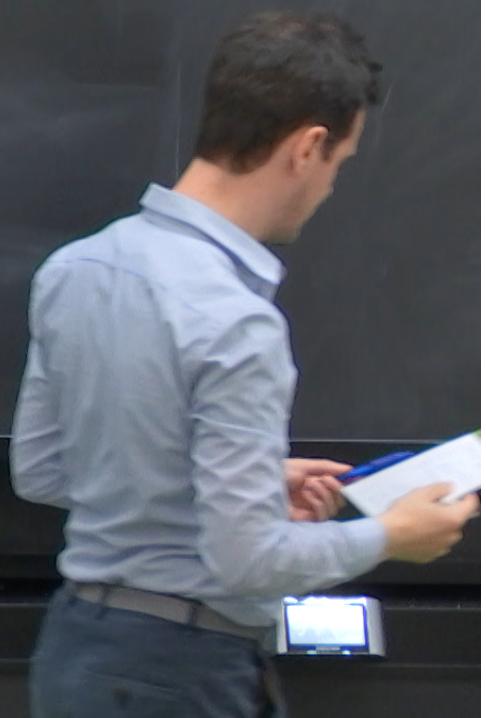
URL: <http://pirsa.org/20030031>



DENIS ROSSET

JULIA

A  
PULL THE LATEST GITHUB COMMITS  
JUPYTERLAB → open EXO\_Installation  
→ run the cells  
→ raise your hand if errors

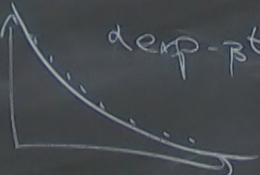


## PAST (Convex) optimization

- $\exists \vec{x} \in \mathbb{R}^n \quad F(\vec{x}) = 0$

$$F: \mathbb{R}^n \rightarrow \mathbb{R}^m$$

- Nonlinear fit



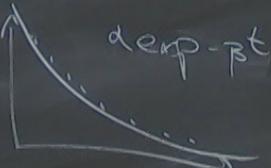
- SAT (Reduce to normal form)

## PAST (Convex) optimization

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- SAT (Reduce to normal form)

- MATLAB  
MAPLE
- ↳ fmincon  
fminunc  
↳ nonlinear optimization

FUTURE

- SDP

LECTURE

QUANTUM INFO

- EXAMPLES TOY PROBLEMS

# OBJECTIVES →

$N=0 \rightarrow$  FEASIBILITY

$N=1 \rightarrow$  Run of The Mill

$N > 1 \rightarrow$  Multi-OB.

(TRADE OFF → PARETO)

Genetic Alg.



## # OBJECTIVES

$N=0 \rightarrow$  FEASIBILITY

$N=1 \rightarrow$  Run of Tree search

$N > 1 \rightarrow$  Multi-OB.

(TRADEOFF  $\rightarrow$  PARETO)

Genetic Alg.

$$\min_{\vec{x} \in \mathbb{R}^n} f(\vec{x})$$

## VARIABLES

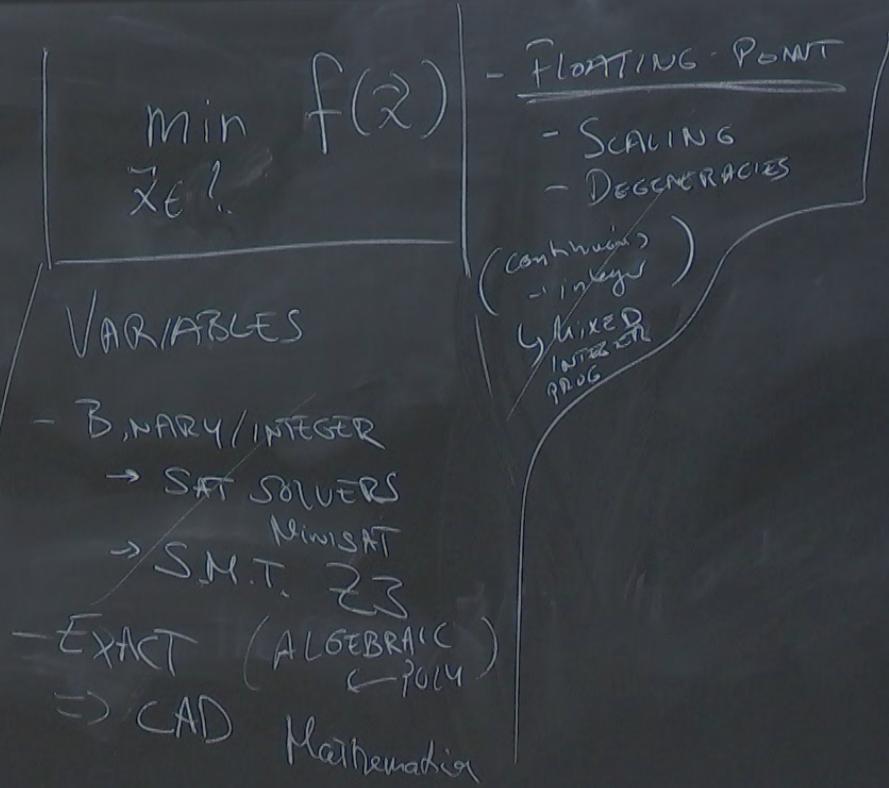
- BINARY/INTEGER
  - $\rightarrow$  SAT SOLVERS
  - $\rightarrow$  S.M.T.  $\mathcal{L}_3$  <sup>MinSAT</sup>

## 4 OBJECTIVES

$N=0 \rightarrow$  FEASIBILITY

$N=1 \rightarrow$  Run of the solver

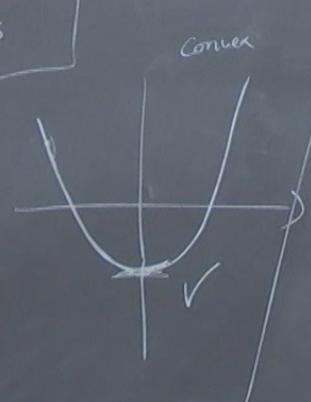
$N \geq 1 \rightarrow$  Multi-obj.  
(TRADE OFF  $\rightarrow$  PARETO)  
Genetic Alg.



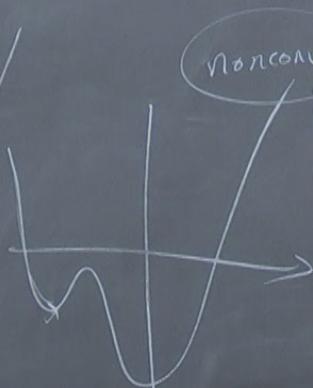
### Floating Point

- SCALING
- DEGENERACIES

(continuous)  
- integer  
Mixed  
integer  
PROG



### OBJECTIVE TYPE



nonconvex  
functions

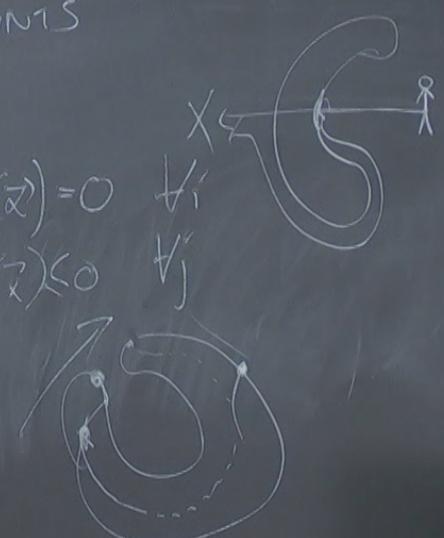
### CONSTRAINTS

$$\min_{x \in \mathbb{R}^n} f(x)$$

s.t.

$$g_i(x) = 0$$

$$h_j(x) \leq 0$$



RAIC  
POLY

uation

## Black-Box

function  $f(x)$

```
!
```

```
return ...  
end
```

```
some for  $g_i, h_j$ 
```

- Use gradient (Hessian 2nd order  $\nabla^2$ )

## CANONICAL FORMS

$$\min_{\vec{x} \in \mathbb{R}^n} \vec{c} \cdot \vec{x}$$

$$\begin{matrix} \vec{A} \vec{x} = \vec{B} \\ \vec{x} \geq 0 \end{matrix}$$

## MODELING FRAMEWORK

CANONICAL

$$f(x)$$

ALGEBRAIC  
DESCRIPTION

• Nonconvex

A. Convex

$$\min_{x \in \mathbb{R}^n} c^T \vec{x}$$

$$Ax = b$$

$$x \geq 0$$

$$g_i, h_j$$

ent (Hessian 2nd order  $\vec{V}^2$ )

## CANONICAL FORMS



$$\min_{\vec{x} \in \mathbb{R}^n} \vec{c} \cdot \vec{x}$$

$$\begin{matrix} \vec{A} \vec{x} = \vec{B} \\ \vec{x} \geq 0 \end{matrix}$$

PYTHON

MATLAB

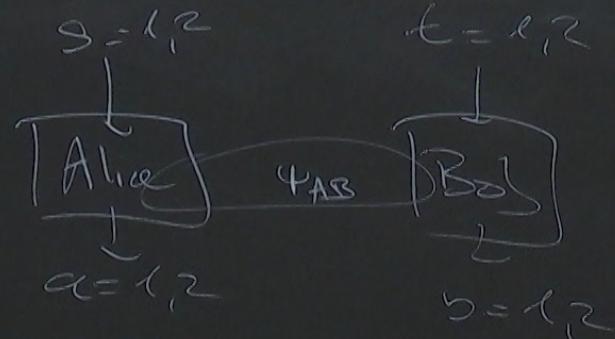
FORTRAN (stale)

R

C/C++

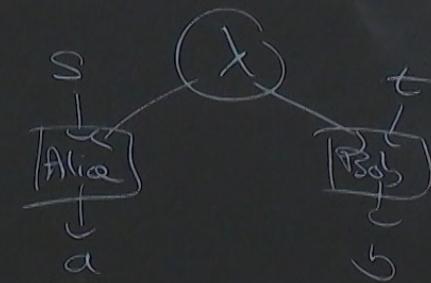
JULIA

MATLAB



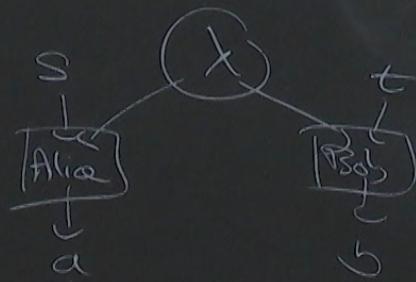
$$\varphi_{AB} \in \mathcal{H}_A \otimes \mathcal{H}_B$$

1964      Bell



$$\begin{cases} a \leftarrow s, \lambda \\ b \leftarrow t, \lambda \end{cases} \times$$

1964 BELL



$$P_{\text{ABST}}^{\text{ab|st}} = \sum_{\lambda} P_{\lambda}^{\text{ab}} P(a|s\lambda) P(b|t\lambda)$$

$$P^{\lambda}$$

$$\begin{cases} a & \text{for } s=1 \\ a & \text{for } s=2 \end{cases}$$

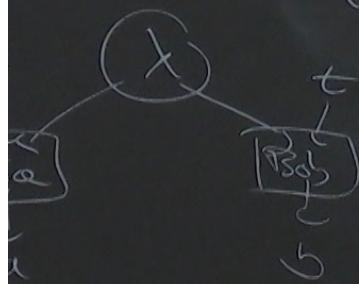
$$\begin{cases} b & \text{for } t=1 \\ b & \text{for } t=2 \end{cases}$$

$$\begin{cases} a \leftarrow s, \lambda \\ b \leftarrow t, \lambda \end{cases} \times$$

$P(a|s\lambda)$  is LOCAL if  $\exists P^B(\lambda), P(a|s\lambda), P(b|\lambda)$

BELL

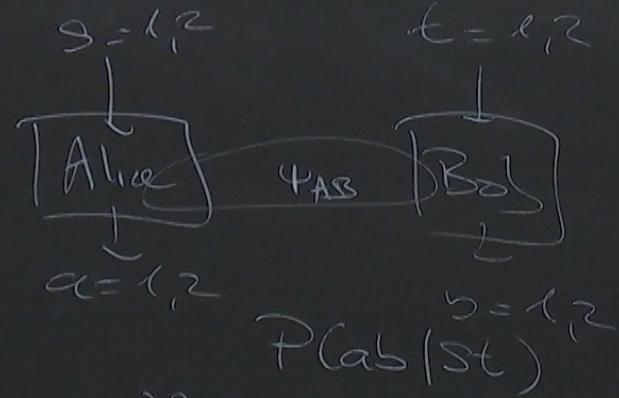
$$(*) P_{AB|ST}^{(ab|st)} = \sum_{\lambda} P_{\lambda}^{(s)} P(a|\lambda) P(b|\lambda)$$



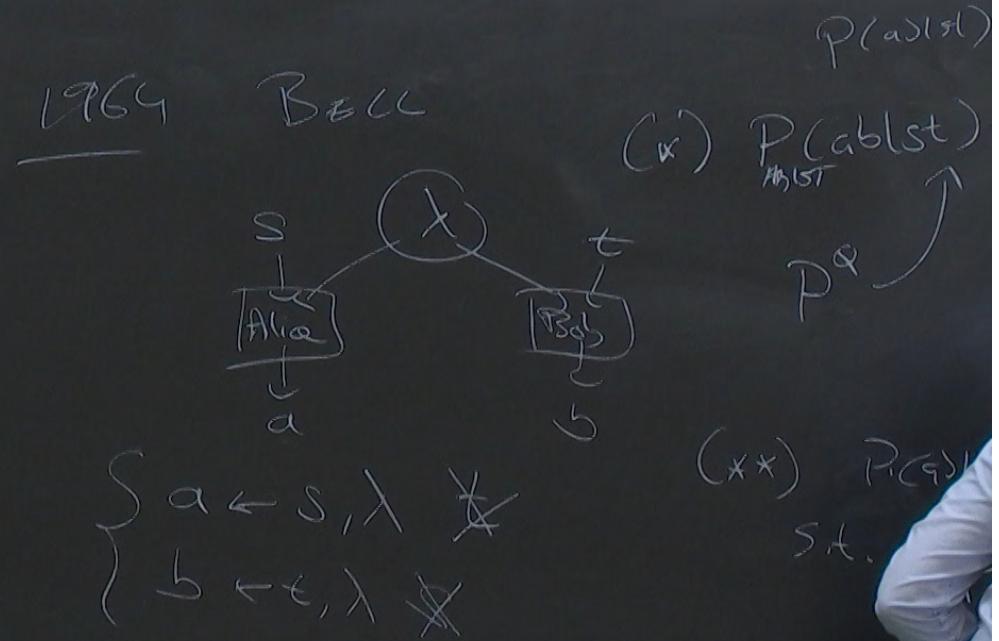
$$\left\{ \begin{array}{l} a \text{ for } s=1 \\ a \text{ for } s=2 \end{array} \right. \quad \left\{ \begin{array}{l} b \text{ for } t=1 \\ b \text{ for } t=2 \end{array} \right.$$

(\*\*)  $P(a|s\lambda)$  is LOCAL if  $\exists P_{A_1 A_2 B_1 B_2}(a_1 a_2 | b_1 b_2)$

s.t.  $P(ab|st) = \sum_{a_1 a_2 b_1 b_2} P(a_1 a_2 | b_1 b_2) \delta[a=a_s] \delta[b=b_t]$

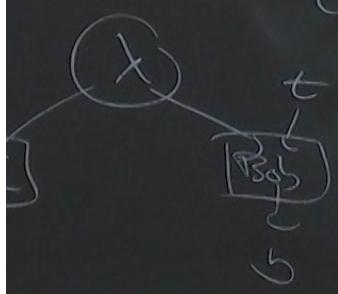


$$\varphi_{AB} \in \mathcal{H}_A \otimes \mathcal{H}_B$$



$P(a|st)$  is LOCAL if  $\exists P(x), P(a|s\lambda), P(b|\epsilon\lambda)$

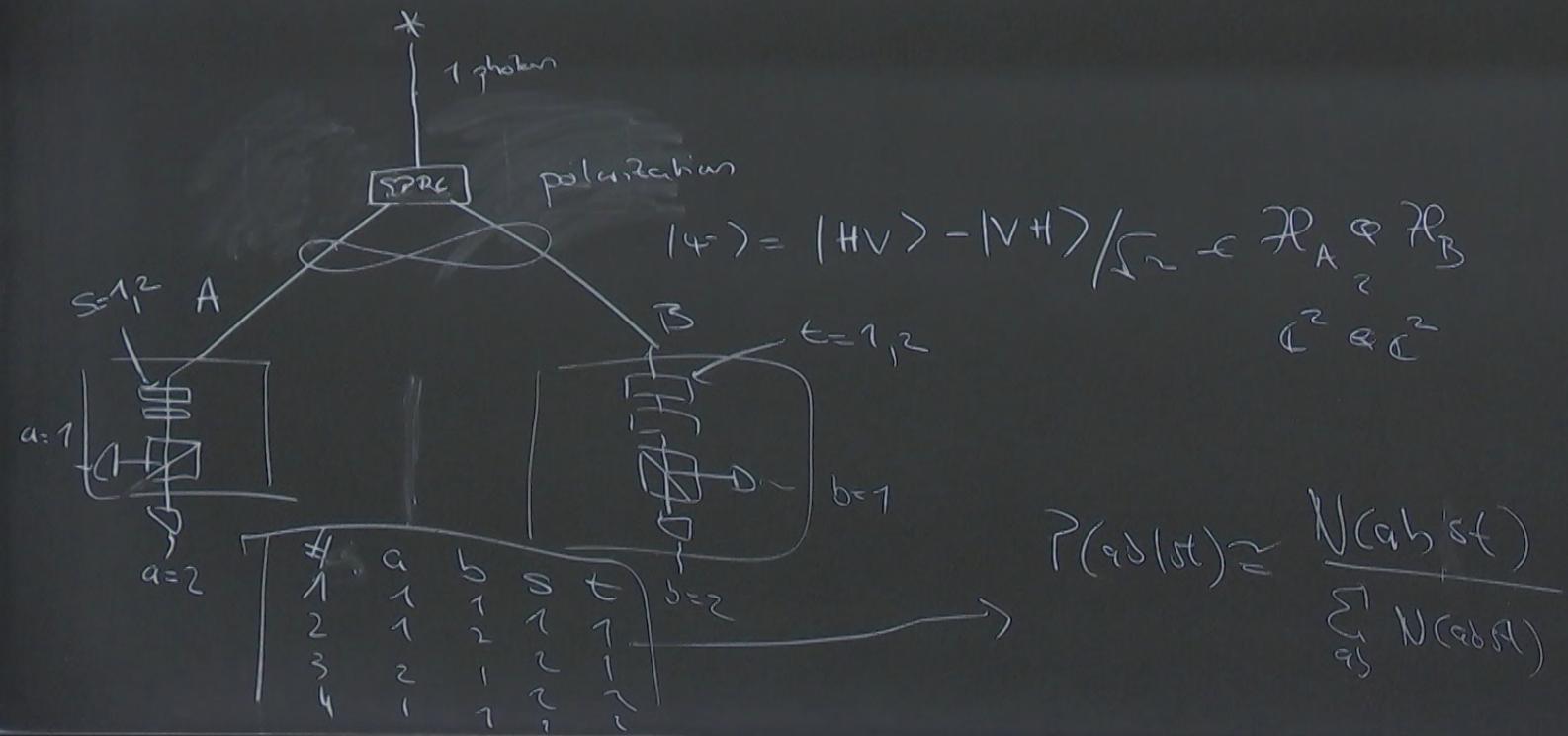
(\*)  $P_{\text{ABST}}(ab|st) = \sum_{\lambda} P(\lambda) P(a|s\lambda) P(b|\epsilon\lambda)$



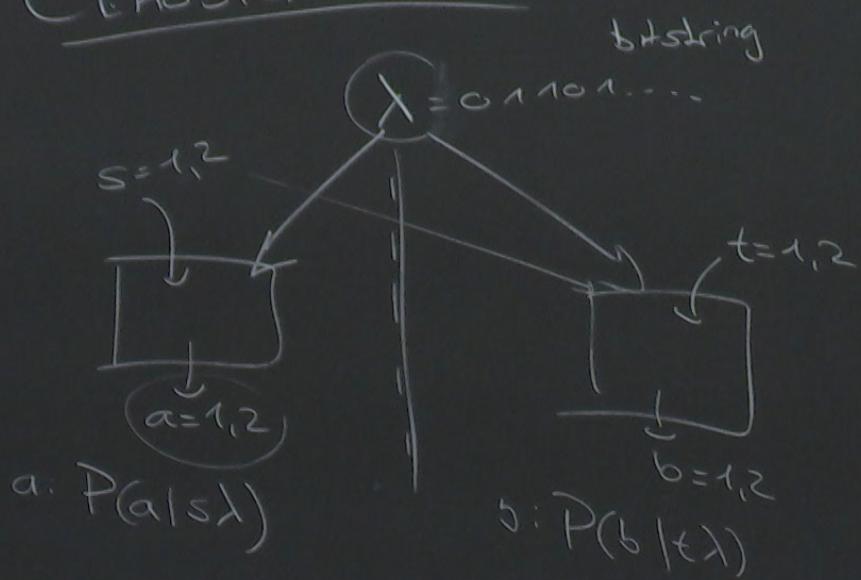
$$P^s \left( \begin{array}{ll} a & \text{for } s=1 \\ a & \text{for } s=2 \end{array} \right) \left( \begin{array}{ll} b & \text{for } t=1 \\ b & \text{for } t=2 \end{array} \right)$$

(\*\*)  $P_{\text{ABST}}(ab|st)$  is LOCAL if  $\exists P_{A_1 A_2 B_1 B_2}(a_1 a_2, b_1 b_2)$

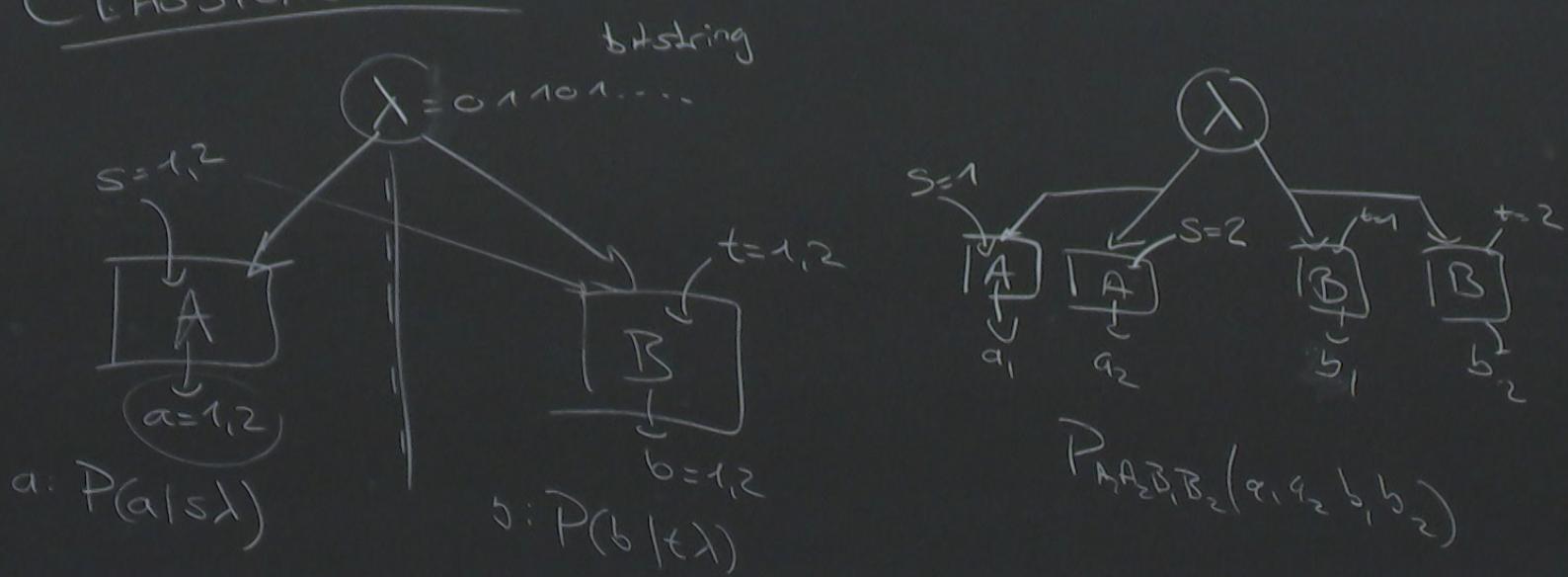
s.t.  $P(ab|st) = \sum_{a_1 a_2 b_1 b_2} P(a_1 a_2 b_1 b_2) \delta[a=a_2] \delta[b=b_2]$



## CLASSICAL MODEL



## CLASSICAL MODEL



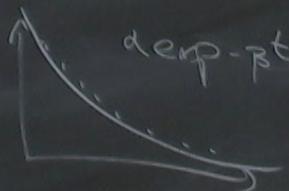
$$\begin{array}{c} \alpha=1,2 \\ \downarrow \\ \text{state} \end{array} \quad \left| \begin{array}{c} \uparrow \\ b=1,2 \end{array} \right. \quad \begin{array}{cccc} a_1 & a_2 & b_1 & b_2 \\ \downarrow & \downarrow & \downarrow & \downarrow \\ P_{AABB}(a_1, a_2, b_1, b_2) \end{array}$$

(Convex) optimization

$$F(\vec{x}) = 0$$

$$F: \mathbb{R}^n \rightarrow \mathbb{R}^m$$

or fit



(Reduce to normal form)

function

function  $\leftarrow$  nonlinear optimization

$$\left\{ \begin{array}{l} |\psi_A\rangle \in \mathbb{C}^2 \leftarrow \{|0\rangle, |1\rangle\} \\ \langle e_A | \psi_A \rangle = 1 \\ e^{i\alpha} |\psi_A\rangle \sim |\psi_A\rangle \end{array} \right. \quad \left| \begin{array}{l} |\psi_B\rangle \leftarrow \beta_1, \beta_2 \\ \left\{ \begin{array}{l} |\psi_A\rangle = \cos \alpha_1 |0\rangle + e^{i\alpha_2} \sin \alpha_1 |1\rangle \\ |\psi_A\rangle_L = -\sin \alpha_1 |0\rangle + e^{i\alpha_2} \cos \alpha_1 |1\rangle \end{array} \right. \\ \langle \psi_A | \psi_A \rangle_L \\ \cdot | \langle \psi_A | \psi_B \rangle_L |^2 \end{array} \right. \quad \text{prob.} \\ |\psi\rangle = |\psi_1\rangle - |\psi_0\rangle / \sqrt{2}$$

File Edit View Run Kernel Git Tabs Settings Help

/ ... / convexcourse / Module1 /

Name	Last Modified
Ex0_Installation.ipynb	3 hours ago
<b>Ex1a_Nonlinear.ipynb</b>	3 hours ago
Ex1b_Nonlinear_JuMP.ipynb	3 hours ago
Ex2_Visibility.ipynb	3 hours ago
octave-workspace	3 hours ago

Packages:

- **NLOpt** Powell's derivative-free algorithms
- **Optim** Gradient-based algorithms, autodifferentiation support

```
[1]: using NLOpt
using Optim
using Printf
```

## Nonlinear unconstrained optimization

Example: projective measurements on the singlet state  $|\Psi^-\rangle = |01 - 10\rangle/\sqrt{2} \in \mathcal{H}_A \otimes (\mathcal{H}_B)$ .

A for Alice and B for Bob.

We parameterize local measurements by qubit states.

$$|\vec{\phi}\rangle = \begin{pmatrix} \cos \phi_1 \\ e^{i\phi_2} \sin \phi_1 \end{pmatrix}, \quad |\vec{\phi}\rangle_{\perp} = \begin{pmatrix} -\sin \phi_1 \\ e^{i\phi_2} \cos \phi_1 \end{pmatrix}$$

There are two measurement settings indexed by  $s = 1, 2$  on  $\mathcal{H}_A$ , corresponding to two projectors  $\{|\alpha_1\rangle, |\alpha_1\rangle_{\perp}\}$  and  $\{|\alpha_2\rangle, |\alpha_2\rangle_{\perp}\}$ , and two measurement settings indexed by  $t = 1, 2$  on  $\mathcal{H}_B$ , corresponding to  $\{|\beta_1\rangle, |\beta_1\rangle_{\perp}\}$  and  $\{|\beta_2\rangle, |\beta_2\rangle_{\perp}\}$ .

The measurement outcomes are 1-based (Julia, Matlab), so that  $a = 1$  corresponds to  $|\alpha_1\rangle$  and  $a = 2$  to  $|\alpha_2\rangle_{\perp}$ . The same for Bob: for  $b = 1$  corresponds to  $|\beta_1\rangle$  and  $b = 2$  to  $|\beta_2\rangle_{\perp}$ .

Then we consider the joint, conditional probability distribution

$$P_{AB|ST}(a, b|s, t)$$

. We compute using Born's rule:

$$P_{AB|ST}(1, 1|s, t) = (\langle \alpha_s | \otimes \langle \beta_t |) |\Psi^-\rangle$$

$$P_{AB|ST}(2, 1|s, t) = (\langle \alpha_s |_{\perp} \otimes \langle \beta_t |) |\Psi^-\rangle$$

$$P_{AB|ST}(1, 2|s, t) = (\langle \alpha_s | \otimes \langle \beta_t |_{\perp}) |\Psi^-\rangle$$

$$P_{AB|ST}(2, 2|s, t) = (\langle \alpha_s |_{\perp} \otimes \langle \beta_t |_{\perp}) |\Psi^-\rangle$$

We want to maximize the CHSH expression:

$$C = \sum_{abst} (-1)^{(a-1)+(b-1)+(s-1)(t-1)} P_{AB|ST}(a, b|s, t)$$

```
[10]: function singlet_proj_prob(x)
    # Computes the joint probability distribution given by two projective measurements on each subsystem of a singlet state
    P = zeros(eltype(x), (2, 2, 2, 2));
    A = zeros(Complex{eltype(x)}[], (2, 2, 2));
    B = zeros(Complex{eltype(x)}[], (2, 2, 2));
    A[:, 1, 1] = [ cos(x[1])           sin(x[1])];
    A[:, 2, 1] = [-sin(x[1])];
```

The screenshot shows a Jupyter Notebook interface with the following details:

- File Bar:** File, Edit, View, Run, Kernel, Git, Tabs, Settings, Help.
- Toolbar:** +, ☰, ⌂, C, ⌘.
- Left Sidebar:** Shows a file tree with the path /.../convexcourse/Module1/. The sidebar includes icons for file operations like New, Open, Save, and a search bar labeled "abst".
- Tab Bar:** Ex0\_Installation.ipynb, Ex1\_Nonlinear.ipynb, Ex2\_Visibility.ipynb, Ex1a\_Nonlinear.ipynb.
- Code Cell:** [10]:  
A function named singlet\_proj\_prob(x) is defined. The function computes the joint probability distribution given by two projective measurements on each subsystem of a singlet state. It initializes matrices P, A, and B with zeros. It then defines the columns of A and B as 2x2 matrices of trigonometric functions of x[1] through x[4]. A nested loop iterates over indices s and t from 1 to 2, and nested loops iterate over indices a and b from 1 to 2. For each combination of s, t, a, and b, it calculates a matrix product involving A and B, scales it by [0; 1; -1; 0]/sqrt(2), and stores the real part of the result in P[a,b,s,t]. Finally, it returns the matrix P.
- Bottom Status Bar:** 0 \$ 5 ⚙ Julia 1.3.1 | Idle, Mode: Edit, ⌂, Ln 19, Col 29, Ex1a\_Nonlinear.ipynb.

File Edit View Run Kernel Git Tabs Settings Help

Ex0\_Installation.ipynb Ex1\_Nonlinear.ipynb Ex2\_Visibility.ipynb Ex1a\_Nonlinear.ipynb Julia 1.3.1

/ ... / convexcourse / Module1 / Name

- Ex0\_Installation.ipynb
- Ex1a\_Nonlinear.ipynb**
- Ex1b\_Nonlinear\_Ju...
- Ex2\_Visibility.ipynb
- octave-workspace

$|\vec{\phi}\rangle = \begin{pmatrix} \cos \phi_1 \\ e^{i\phi_2} \sin \phi_1 \end{pmatrix}, \quad |\vec{\phi}\rangle_{\perp} = \begin{pmatrix} -\sin \phi_1 \\ e^{i\phi_2} \cos \phi_1 \end{pmatrix}$

There are two measurement settings indexed by  $s = 1, 2$  on  $\mathcal{H}_A$ , corresponding to two projectors  $\{|\alpha_1\rangle, |\alpha_1\rangle_{\perp}\}$  and  $\{|\alpha_2\rangle, |\alpha_2\rangle_{\perp}\}$ , and two measurement settings indexed by  $t = 1, 2$  on  $\mathcal{H}_B$ , corresponding to  $\{|\beta_1\rangle, |\beta_1\rangle_{\perp}\}$  and  $\{|\beta_2\rangle, |\beta_2\rangle_{\perp}\}$ .

The measurement outcomes are 1-based (Julia, Matlab), so that  $a = 1$  corresponds to  $|\alpha_s\rangle$  and  $a = 2$  to  $|\alpha_s\rangle_{\perp}$ . The same for Bob: for  $b = 1$  corresponds to  $|\beta_t\rangle$  and  $b = 2$  to  $|\beta_t\rangle_{\perp}$ .

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$$P_{AB|ST}(a, b | s, t)$$

We compute using Born's rule:

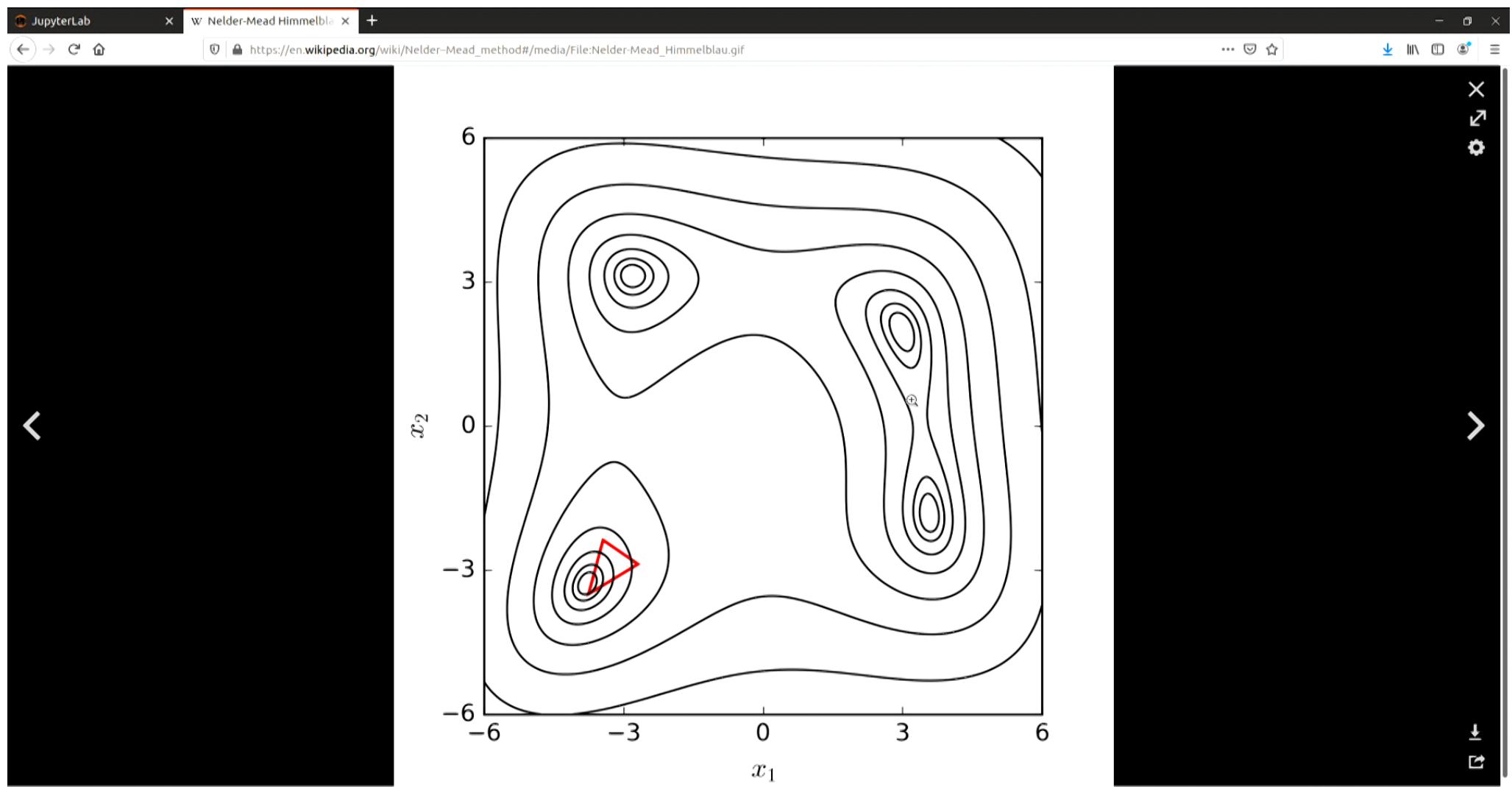
$$\begin{aligned} P_{AB|ST}(1, 1 | s, t) &= (\langle \alpha_s | \otimes \langle \beta_t |) |\Psi^-\rangle \\ P_{AB|ST}(2, 1 | s, t) &= (\langle \alpha_s |_{\perp} \otimes \langle \beta_t |) |\Psi^-\rangle \\ P_{AB|ST}(1, 2 | s, t) &= (\langle \alpha_s | \otimes \langle \beta_t |_{\perp}) |\Psi^-\rangle \\ P_{AB|ST}(2, 2 | s, t) &= (\langle \alpha_s |_{\perp} \otimes \langle \beta_t |_{\perp}) |\Psi^-\rangle \end{aligned}$$

We want to maximize the CHSH expression:

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    A[:, 1, 1] = [ cos(x[1]) sin(x[1])];
    A[:, 2, 1] = [ 0 1];
    A[:, 1, 2] = [ sin(x[1]) -cos(x[1])];
    A[:, 2, 2] = [ 0 1];
    B[:, 1, 1] = [ 1 0];
    B[:, 2, 1] = [ 0 1];
    B[:, 1, 2] = [ 0 1];
    B[:, 2, 2] = [ 1 0];
```

Mode: Command Ln 1, Col 1 Ex1a\_Nonlinear.ipynb



Nelder-Mead animated for the Himmelblau's function

Nicoguaro - Own work

[More details](#)

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