CS492: Probabilistic Programming
Introduction

Hongseok Yang
KAIST

This Review … discusses some of the state-of-the-art advances in the field, namely, probabilistic programming, Bayesian optimization, data compression and automatic model discovery.

Zoubin Gharahmani
2015 Nature Review

What is probabilistic programming?

(Bayesian) probabilistic modelling of data

1. Develop a new probabilistic (generative) model.
2. Design an inference algorithm for the model.
3. Using the algo., fit the model to the data.

(Bayesian) probabilistic modelling of data

in a prob. prog. language

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(Bayesian) probabilistic modelling of data

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as a program

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(Bayesian) probabilistic modelling of data

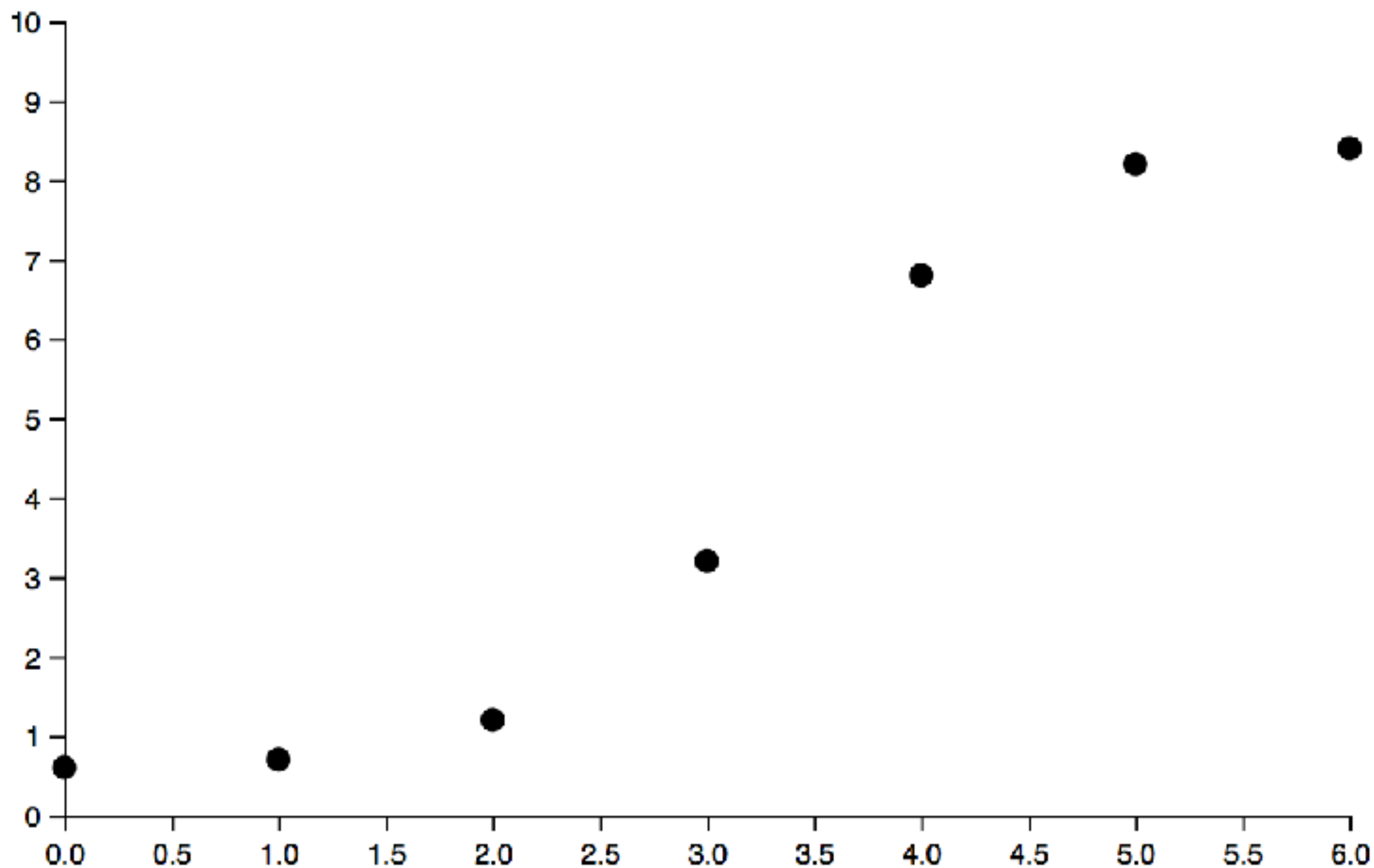
in a prob. prog. language

as a program

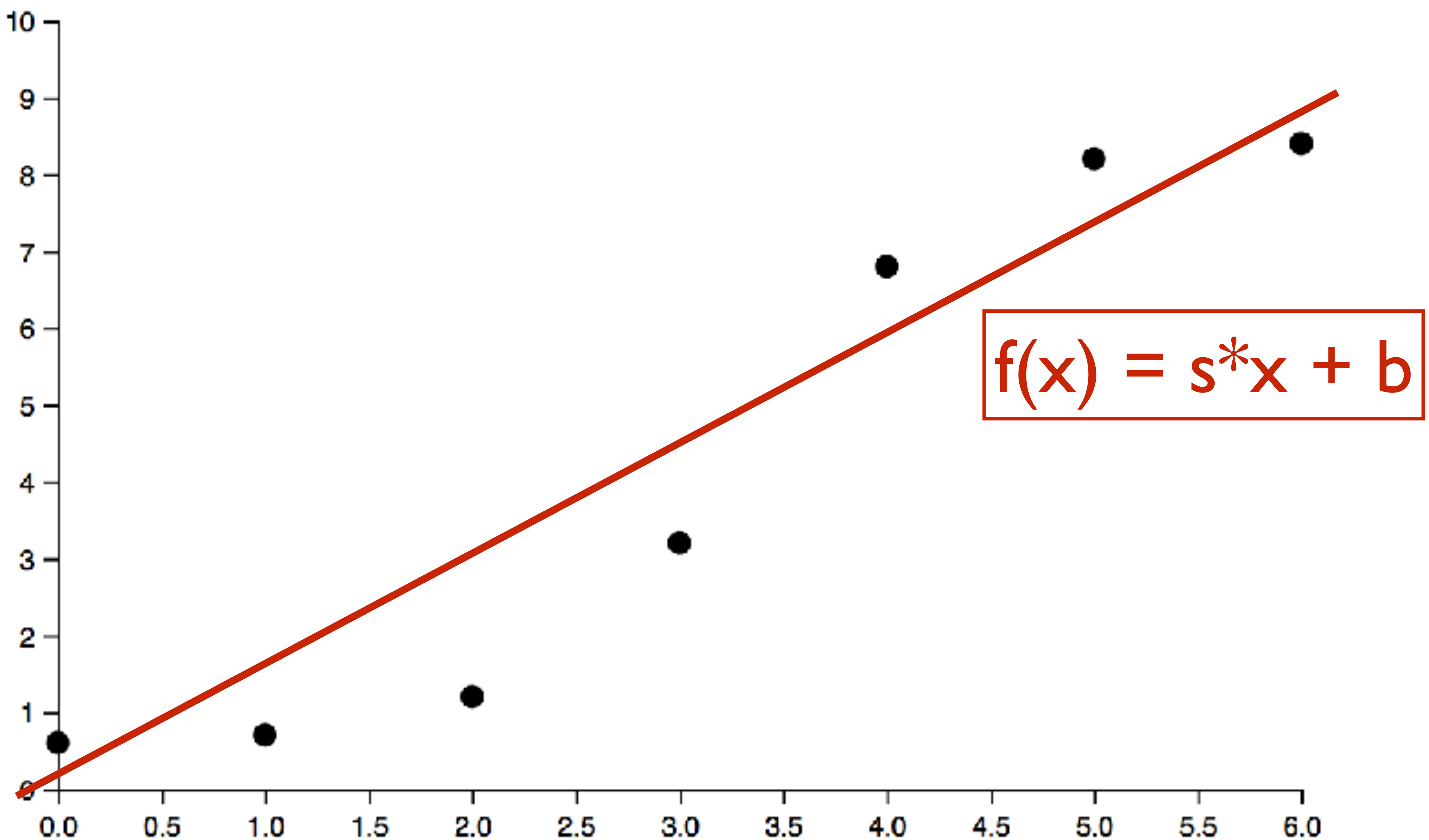
1. Develop a new probabilistic (generative) model.
2. ~~Design an inference algorithm for the model.~~
3. Using ~~the algo~~, fit the model to the data.

a generic inference algo.
of the language

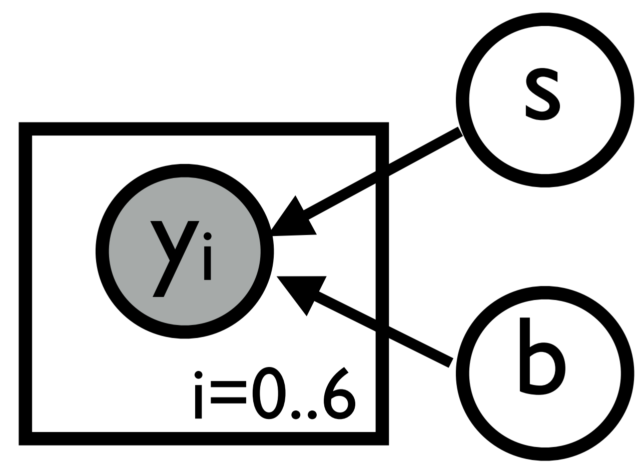
Line fitting



Line fitting



Bayesian generative model



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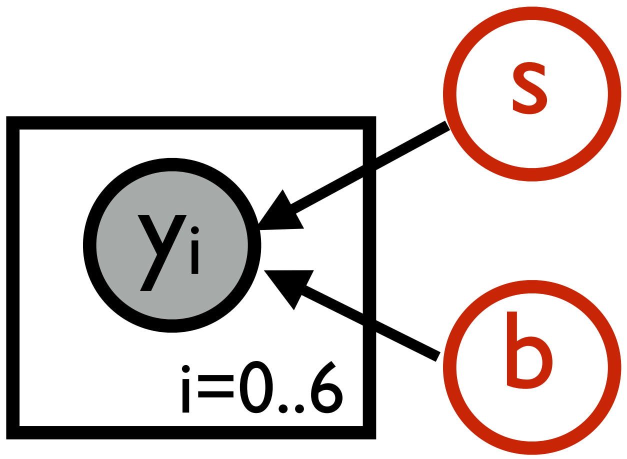
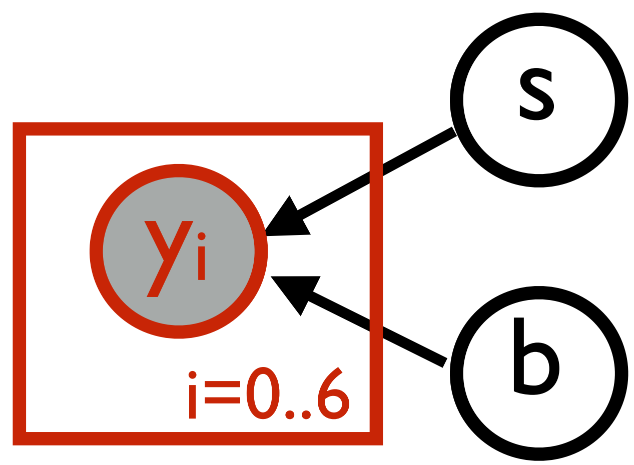


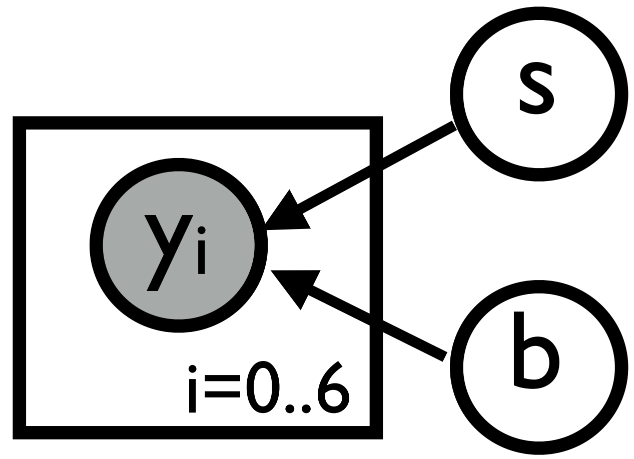

```
s     ~ normal(0, 2)
b     ~ normal(0, 6)
```

Bayesian generative model




```
s      ~ normal(0, 2)
b      ~ normal(0, 6)
f(x)   = s*x + b
yi      ~ normal(f(i), 0.5)
               where i = 0 .. 6
```

Bayesian generative model




```
s     ~ normal(0, 2)
b     ~ normal(0, 6)
f(x)  = s*x + b
y_i   ~ normal(f(i), 0.5)
          where i = 0 .. 6
```

Q: posterior of (s,b) given y_0=0.6, …, y_6=8.4?

Posterior of s and b given y_i's

$$P(s, b \mid y_0, .., y_6) = \frac{P(y_0, .., y_6 \mid s,b) \times P(s,b)}{P(y_0, .., y_6)}$$

Posterior of s and b given y_i's

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(almost) Anglican program

```
(let [s (sample (normal 0 2))
      b (sample (normal 0 6))
      f (fn [x] (+ (* s x) b))]
```

(almost) Anglican program

```
(let [s (sample (normal 0 2))
      b (sample (normal 0 6))
      f (fn [x] (+ (* s x) b))]

    (observe (normal (f 0) .5) .6)
    (observe (normal (f 1) .5) .7)
    (observe (normal (f 2) .5) 1.2)
    (observe (normal (f 3) .5) 3.2)
    (observe (normal (f 4) .5) 6.8)
    (observe (normal (f 5) .5) 8.2)
    (observe (normal (f 6) .5) 8.4)
```

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(let [s (sample (normal 0 2))
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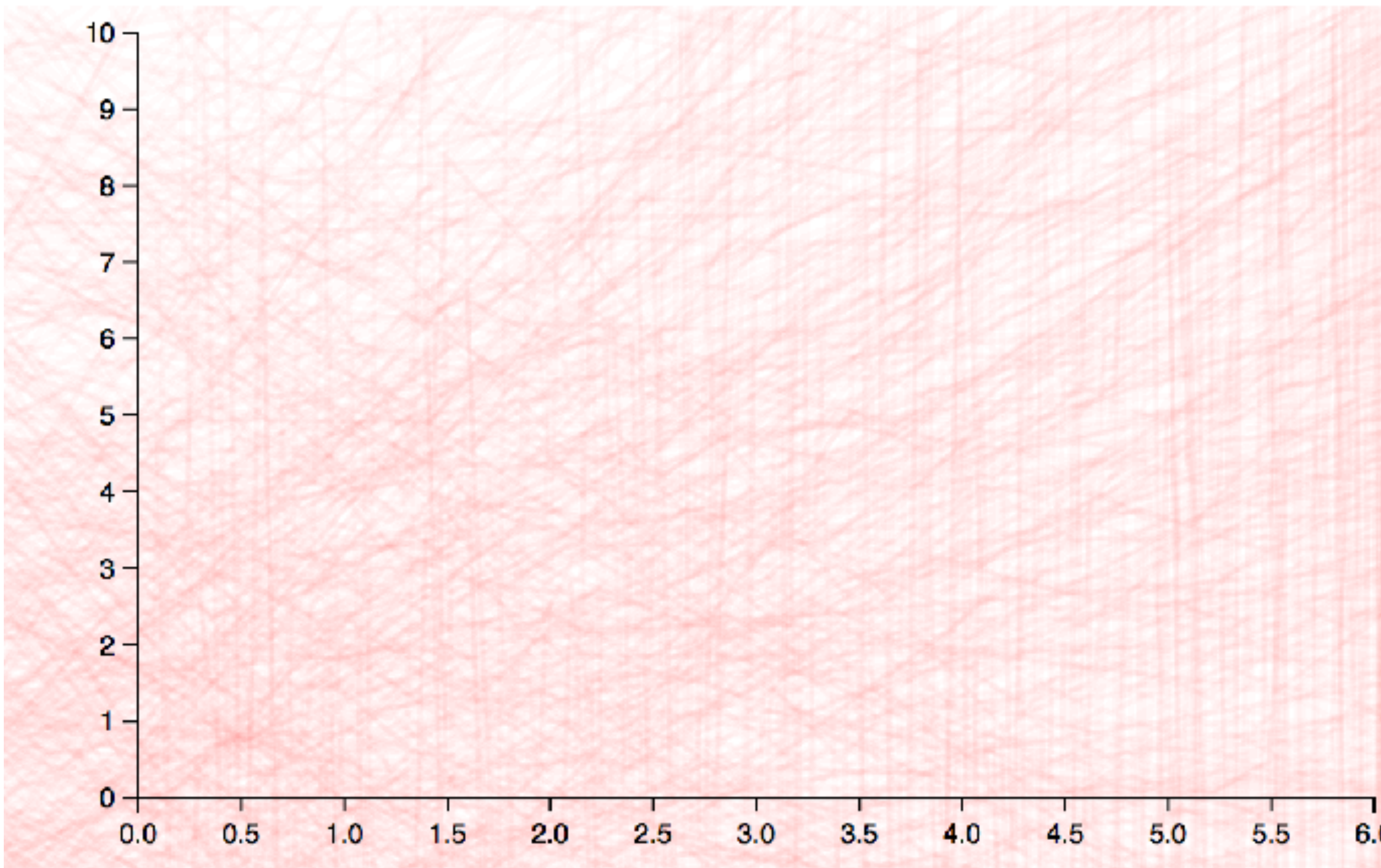
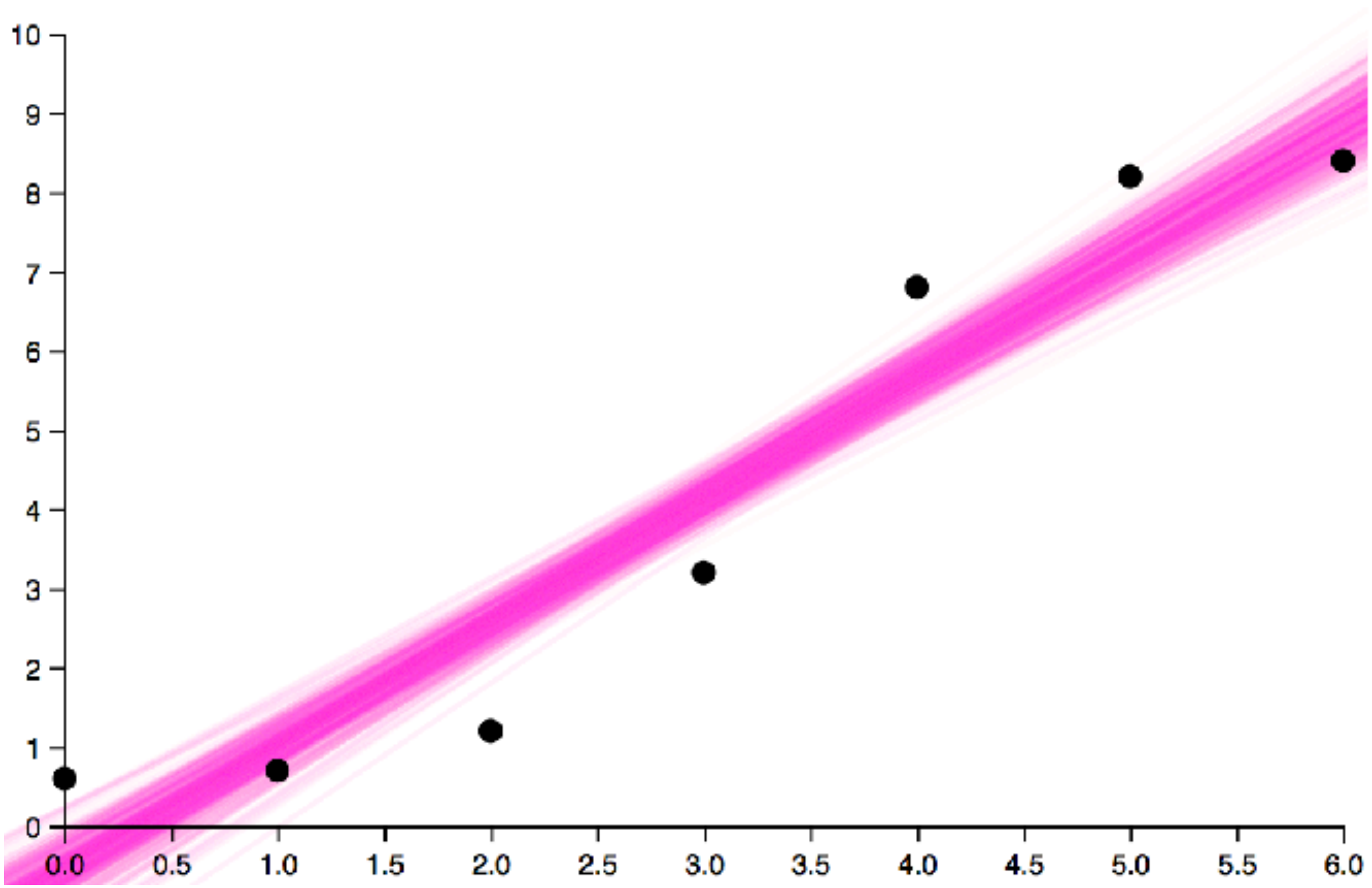
  [s b])
```

NB: (predict :sb [s b]) should be used instead of [s b] in Anglican

Samples from prior



Samples from posterior



Why should one care about prob. programming?

“Because probabilistic programming is a good way to build an AI.” (My ML colleague)

Prob. programming languages enable one to build and explore highly complex models.

```
(let [s (sample (normal 0 2))
      b (sample (normal 0 6))
      f (fn [x] (+ (* s x) b))]

    (observe (normal (f 0) .5) .6)
    (observe (normal (f 1) .5) .7)
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  [s b])
```

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  [s b])
```

Functions as first-class citizen.

```
(let [s (sample (normal 0 2))
      b (sample (normal 0 6))
      f (fn [x] (+ (* s x) b))]

    (observe (normal (f 0) .5) .6)
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```

~~[s b])~~
f)

Functions as first-class citizen.

```
(let [F (fn []
          (let [s (sample (normal 0 2))
                b (sample (normal 0 6))]
            (fn [x] (+ (* s x) b))))
      f (F)]
    (observe (normal (f 0) .5) .6)
    (observe (normal (f 1) .5) .7)
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  [s b])
  f)
```

Functions as first-class citizen.

```
(let [F (fn []
          (let [s (sample (normal 0 2))
                b (sample (normal 0 6))]
            (fn [x] (+ (* s x) b))))
      f (add-change-points F 0 6)]
    (observe (normal (f 0) .5) .6)
    (observe (normal (f 1) .5) .7)
    (observe (normal (f 2) .5) 1.2)
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  [s b])
  f)
```
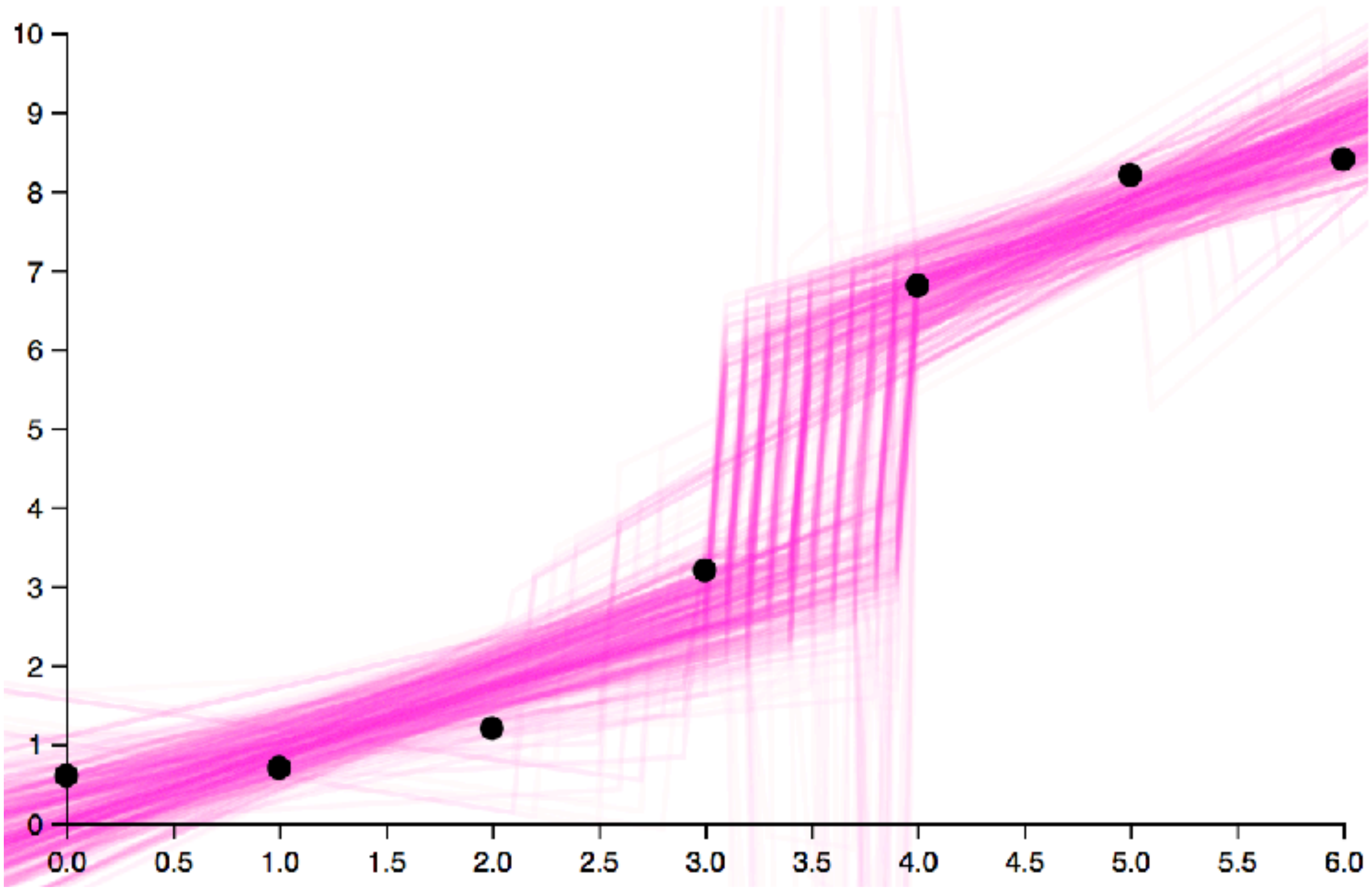

Functions as first-class citizen.

Samples from posterior



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~~[s b])~~

f)

[Q] Change the model so that it finds constant functions with change points.

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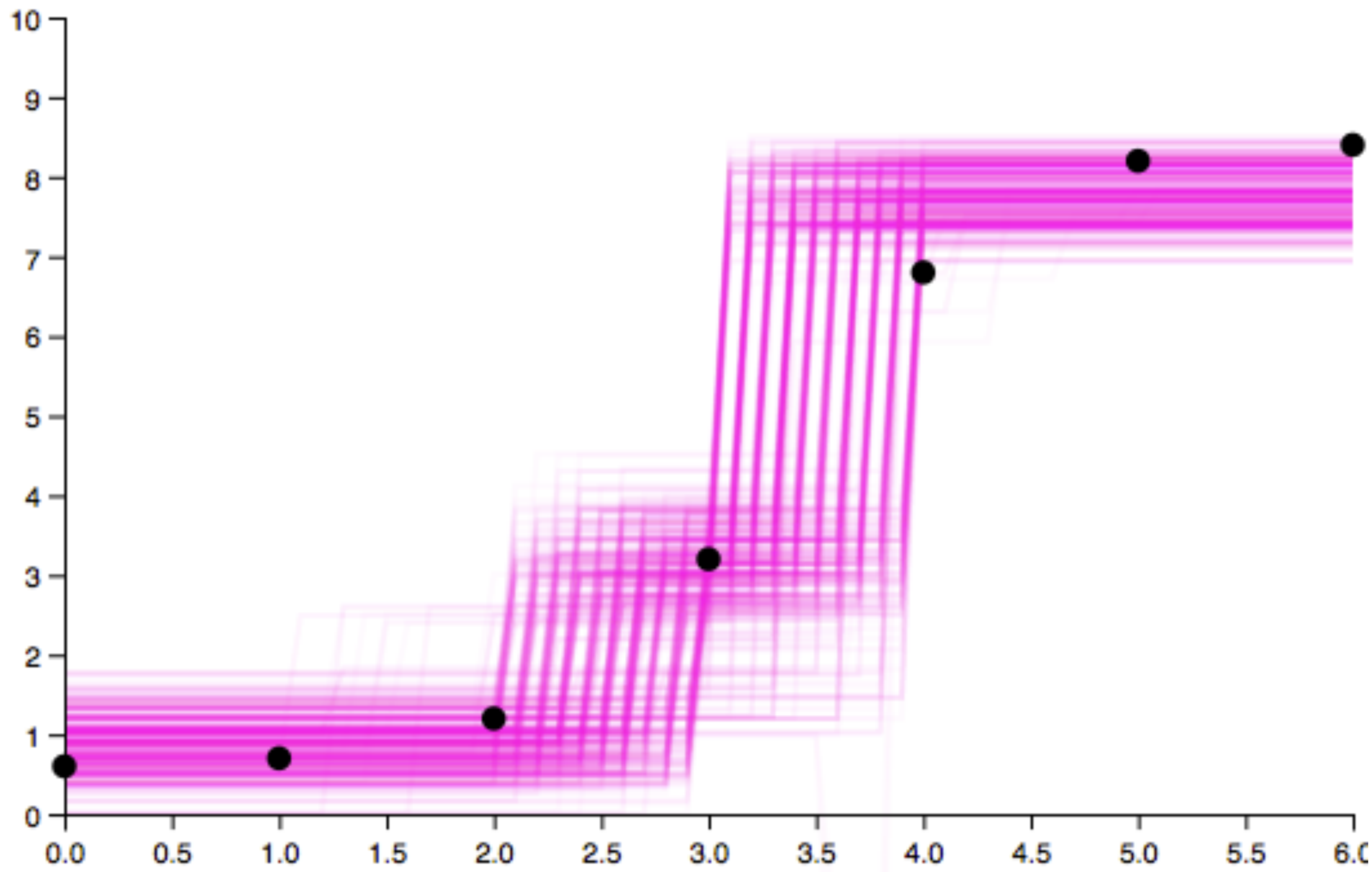
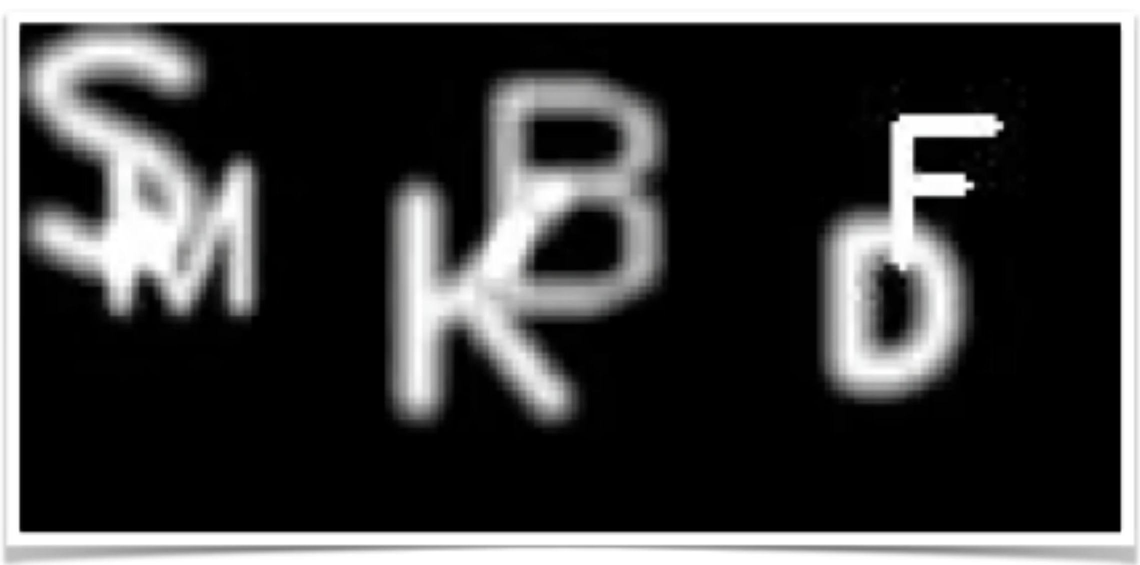


Success story 1: Captcha breaking



SMKBDF

Le, Baydin, Wood [2016]

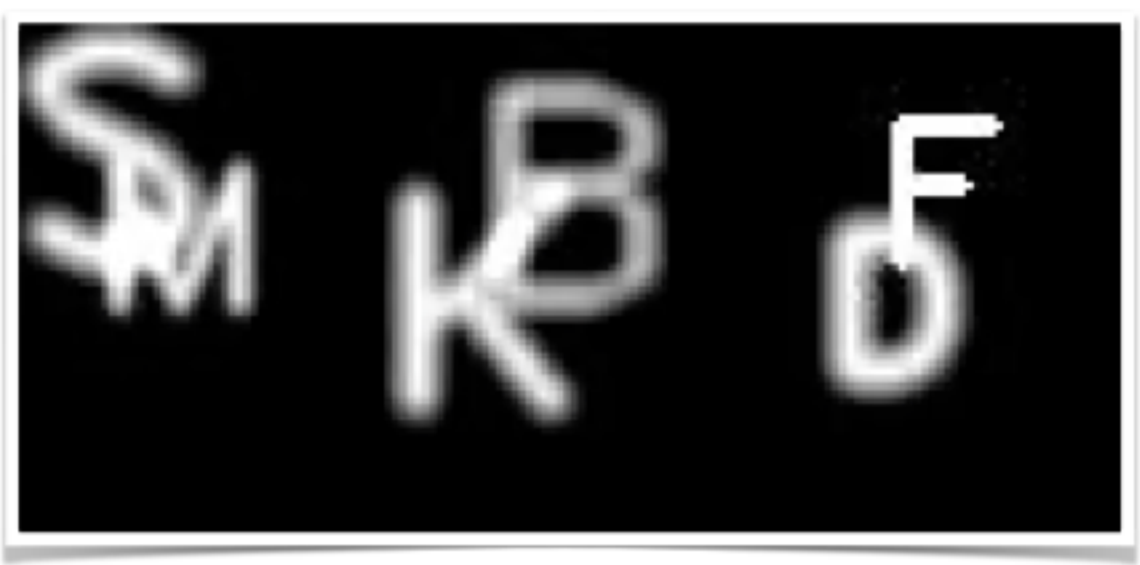
Success story 1:
Captcha breaking

→ SMKBDF

1. Sample a string.

Le, Baydin, Wood [2016]

Success story 1: Captcha breaking

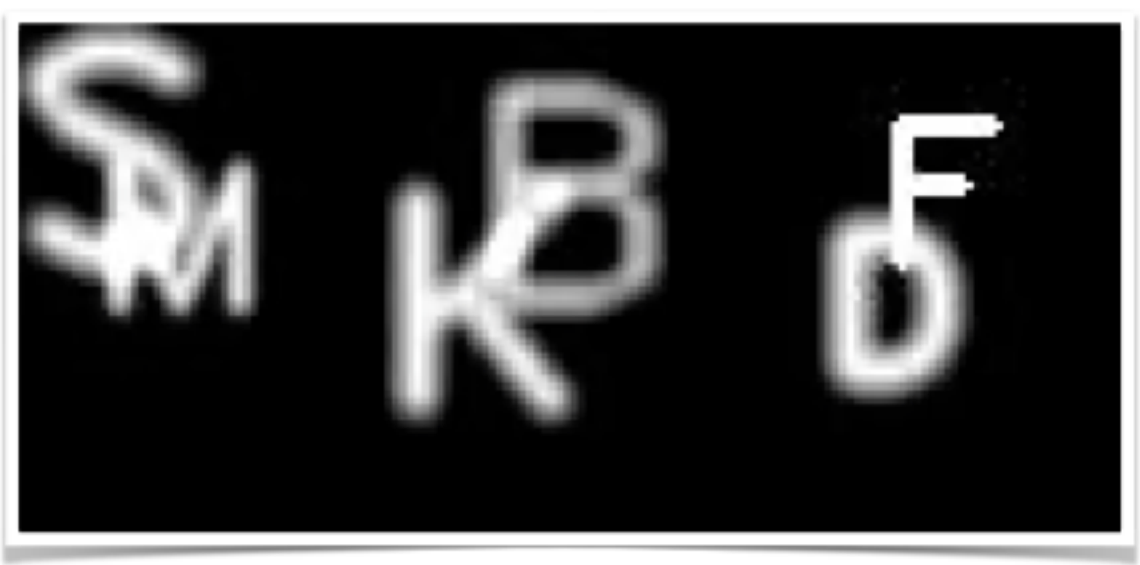


SMKBDF

1. Sample a string.
2. Generate an image.

Le, Baydin, Wood [2016]

Success story 1: Captcha breaking



posterior inference

SMKBDF

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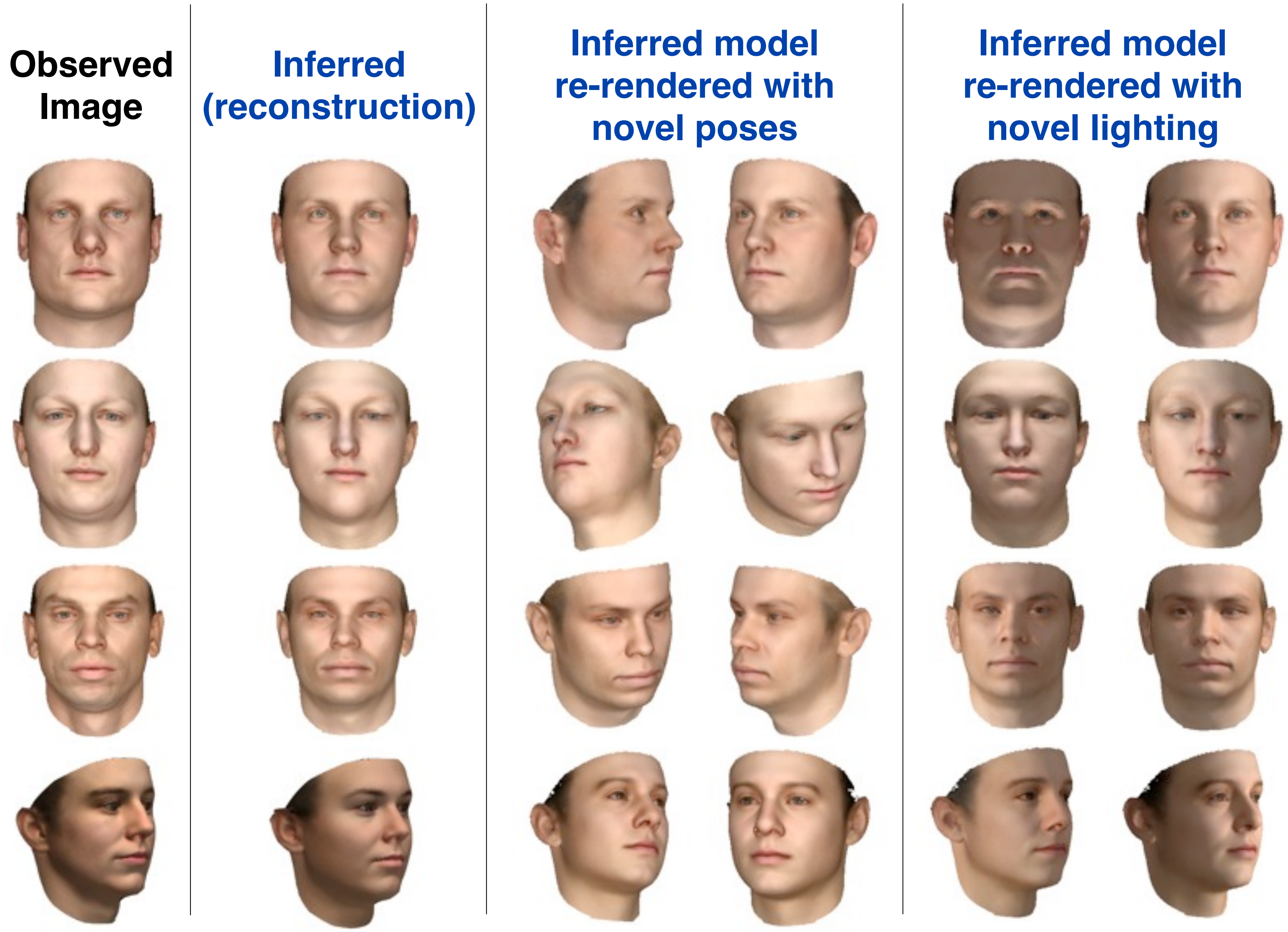
Le, Baydin, Wood [2016]

Success story 2: Inverse graphics



Kulkarni, Kohl, Tenenvaum, Mansinghka [CVPR'15]

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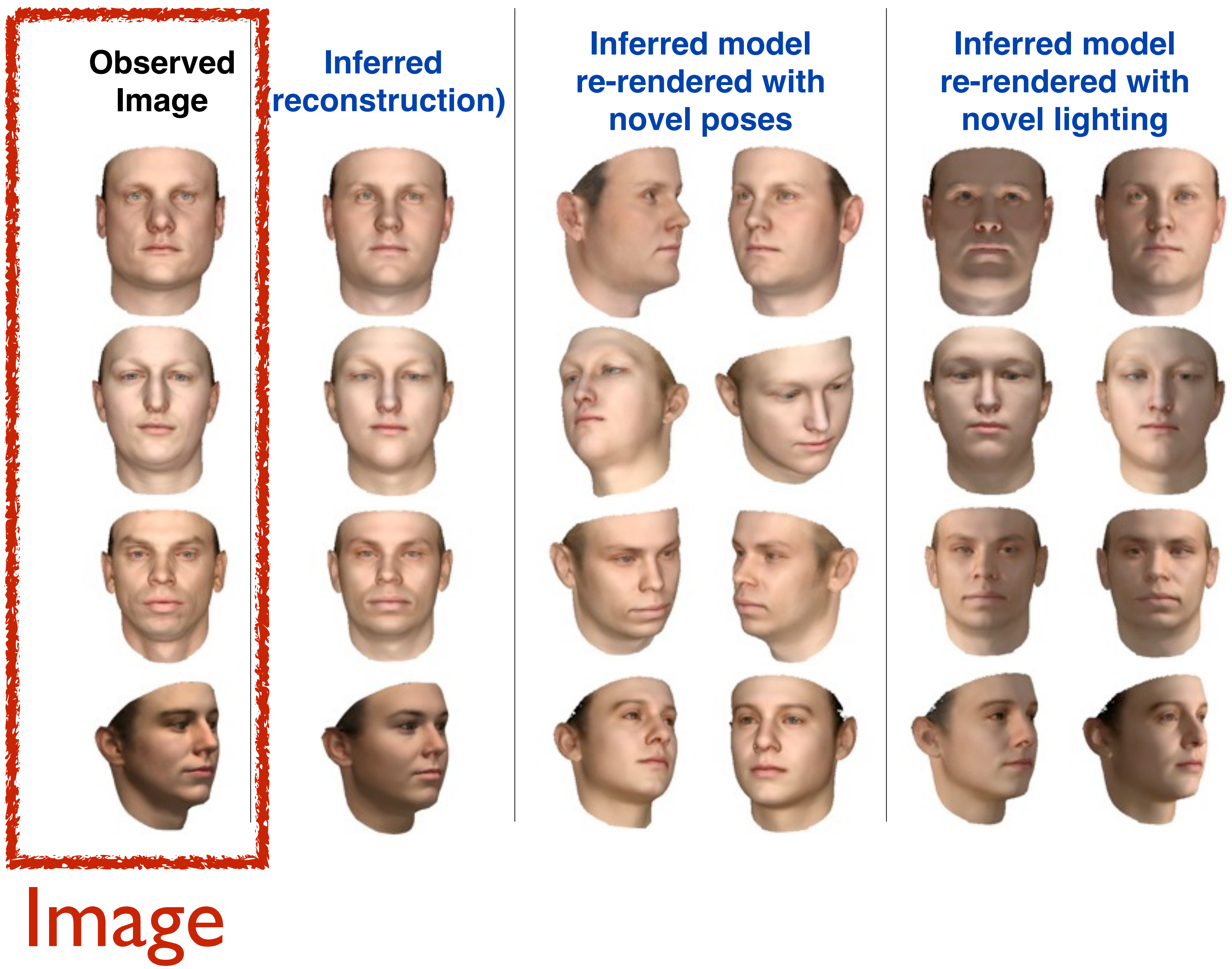

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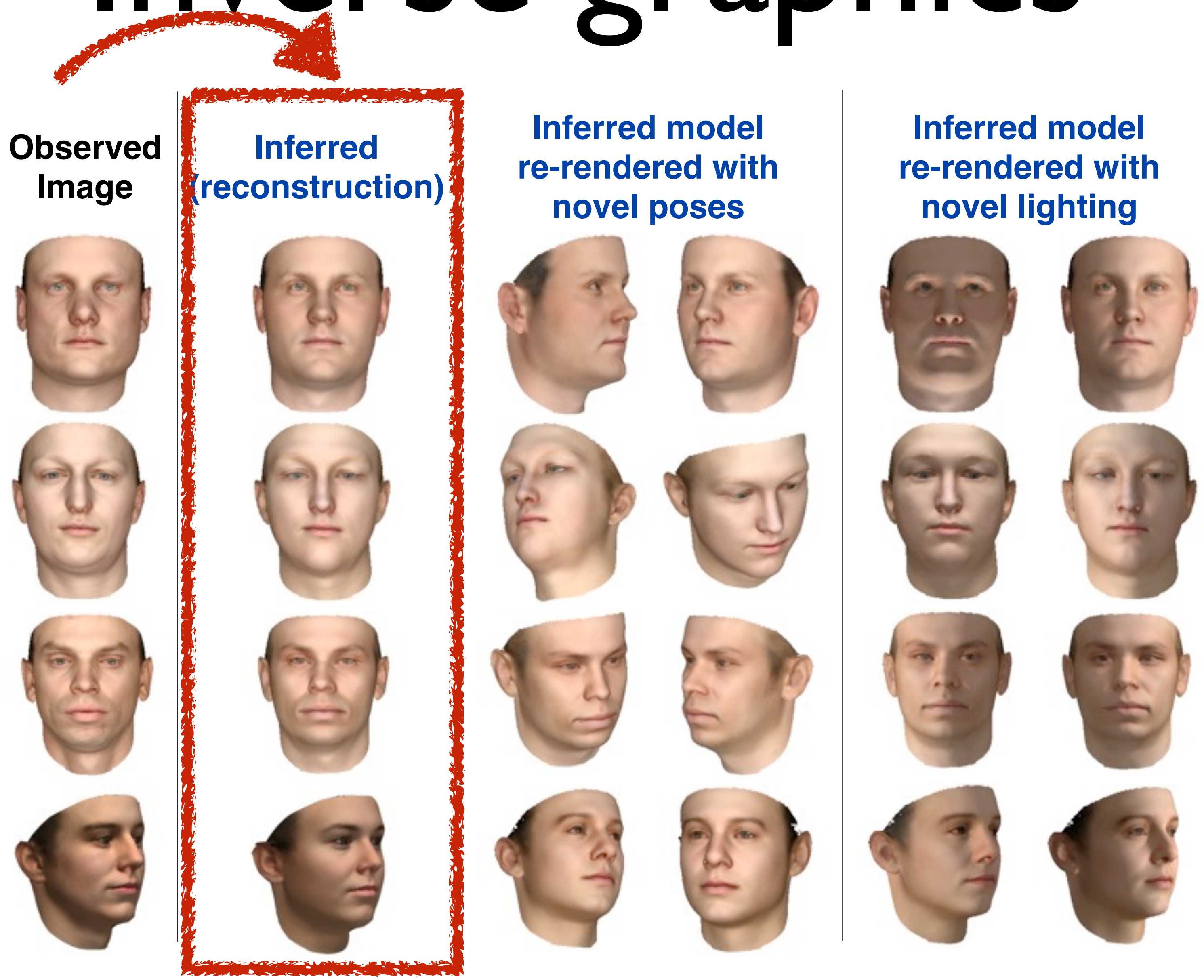
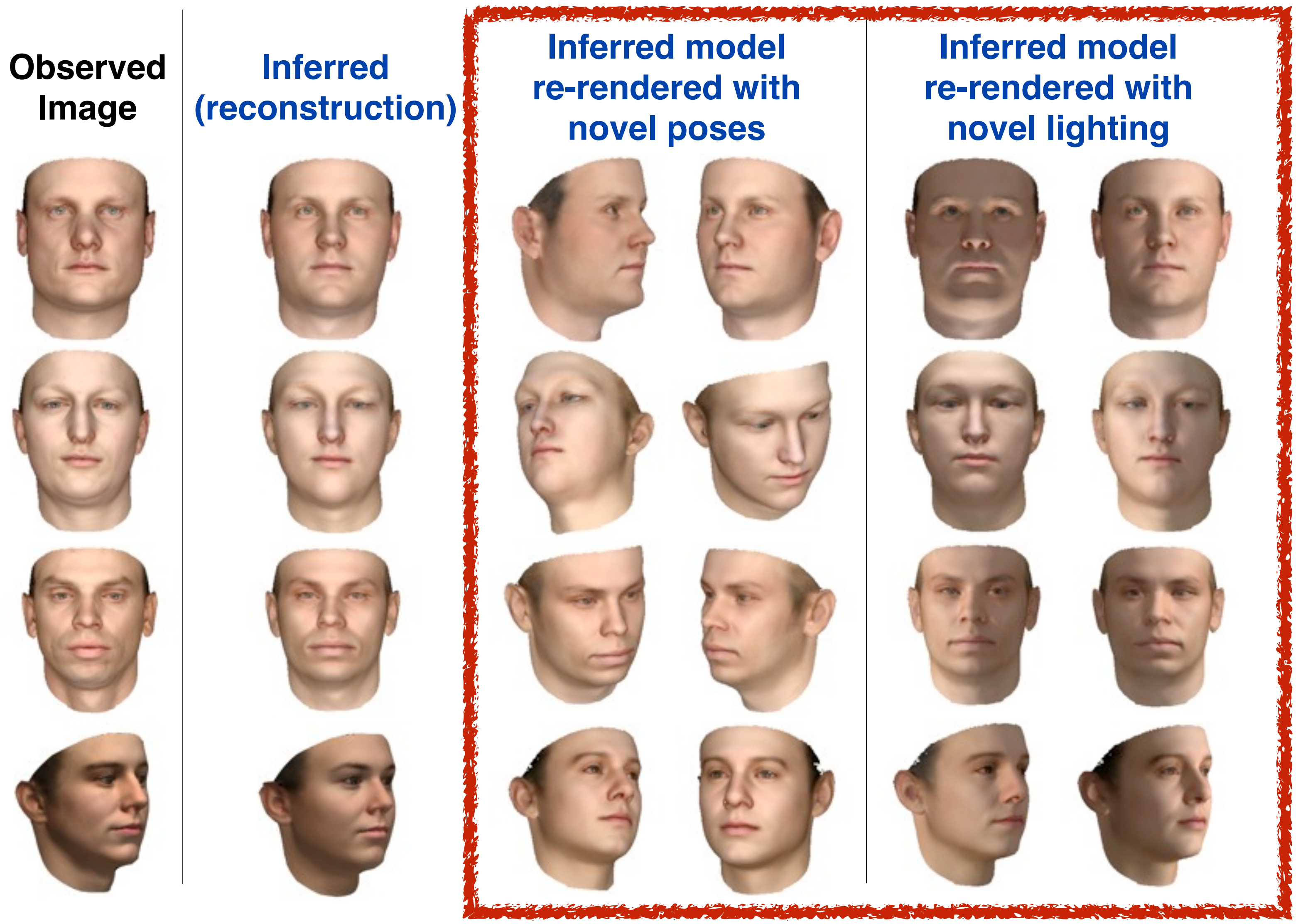


3D model

Kulkarni, Kohl, Tenenvaum, Mansinghka [CVPR'15]

Success story 2: Inverse graphics

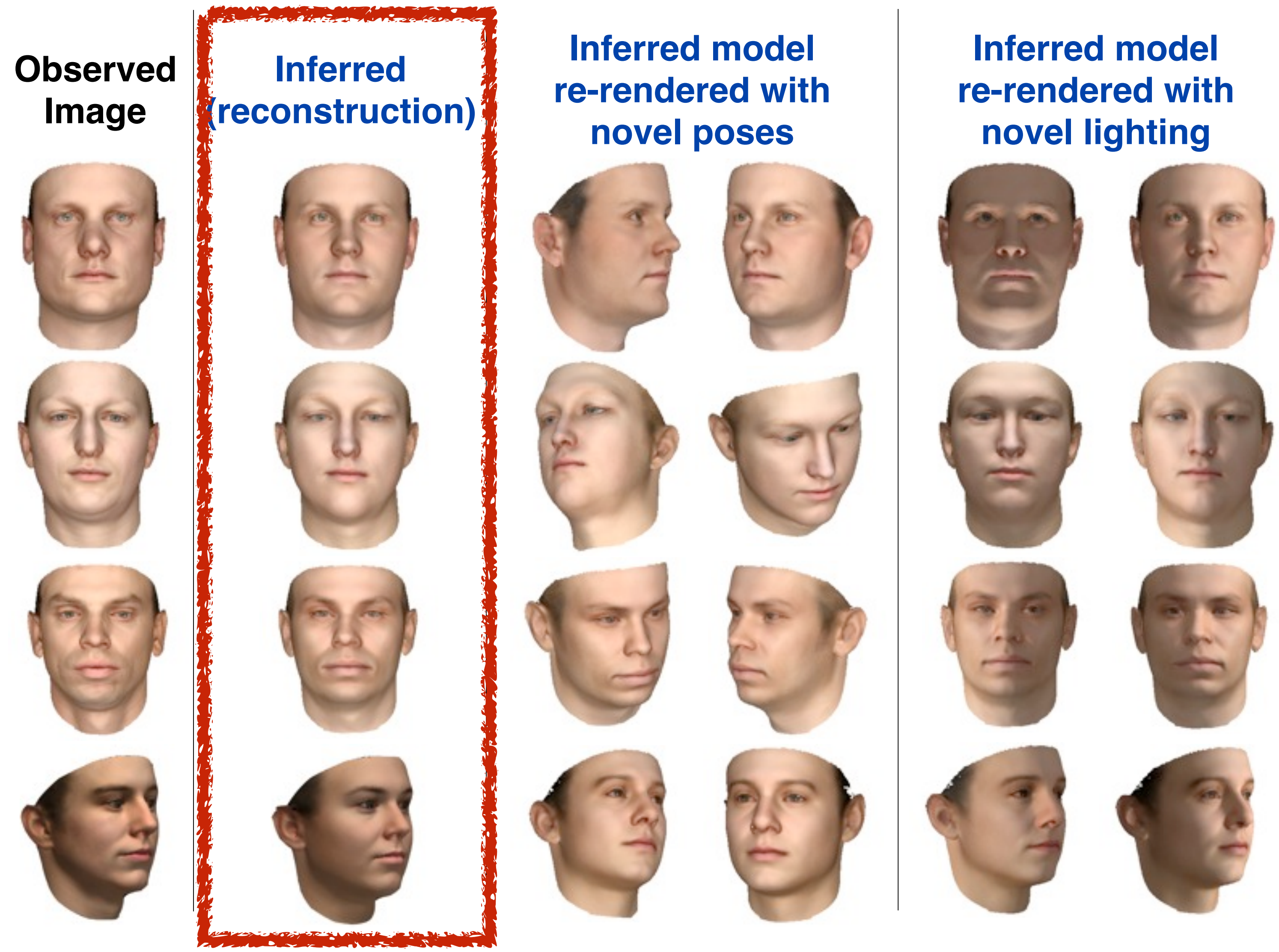


Transformed 3D models

Kulkarni, Kohl, Tenenvaum, Mansinghka [CVPR'15]

S… ss story 2: … e graphics

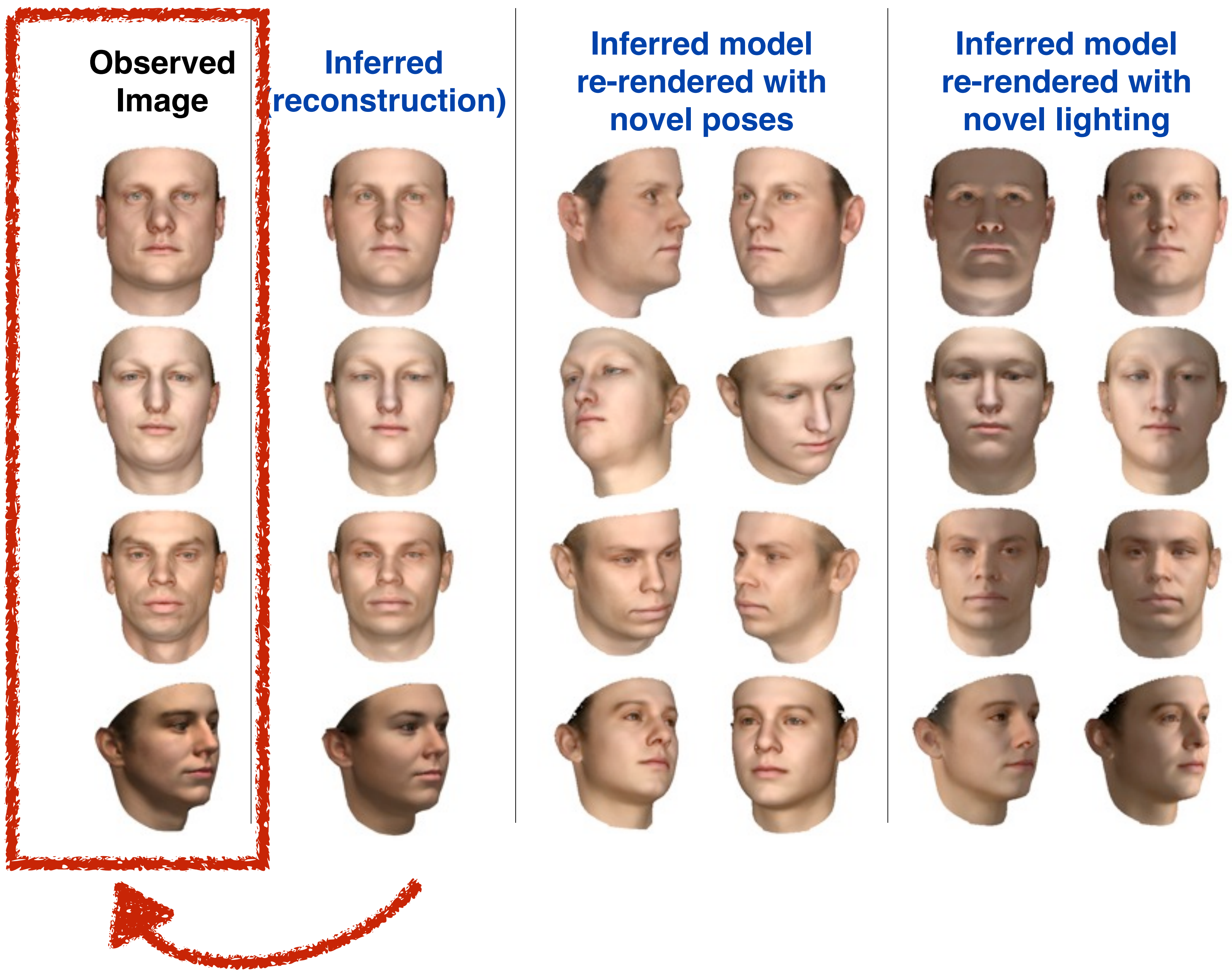
1. Sample a 3D model.



Kulkarni, Kohl, Tenenvaum, Mansinghka [CVPR'15]

1. Sample a 3D model.
2. Generate an image.

S… ss story 2: … e graphics



Kulkarni, Kohl, Tenenvaum, Mansinghka [CVPR'15]

ss story 2: e graphics

1. Sample a 3D model.
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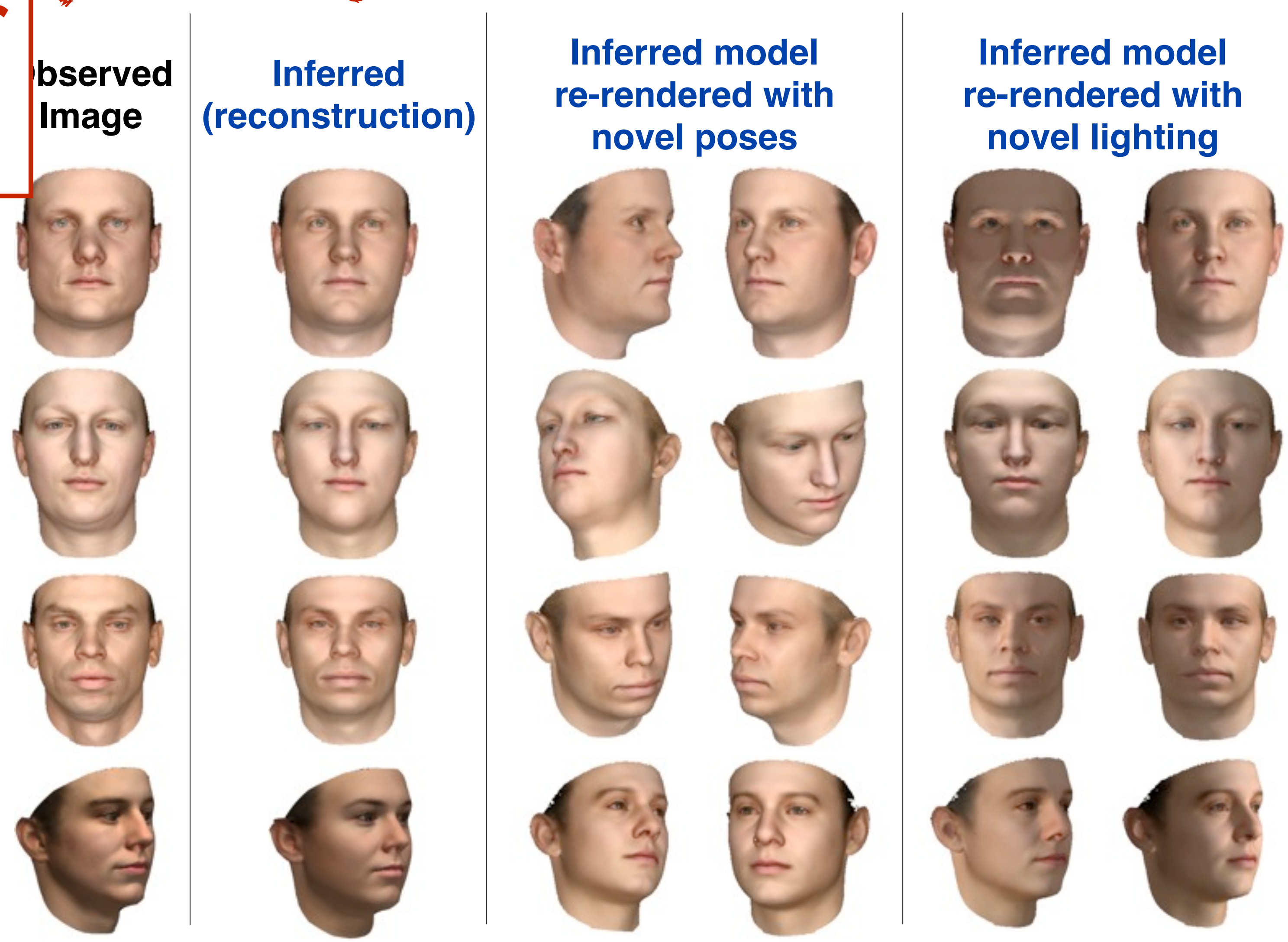
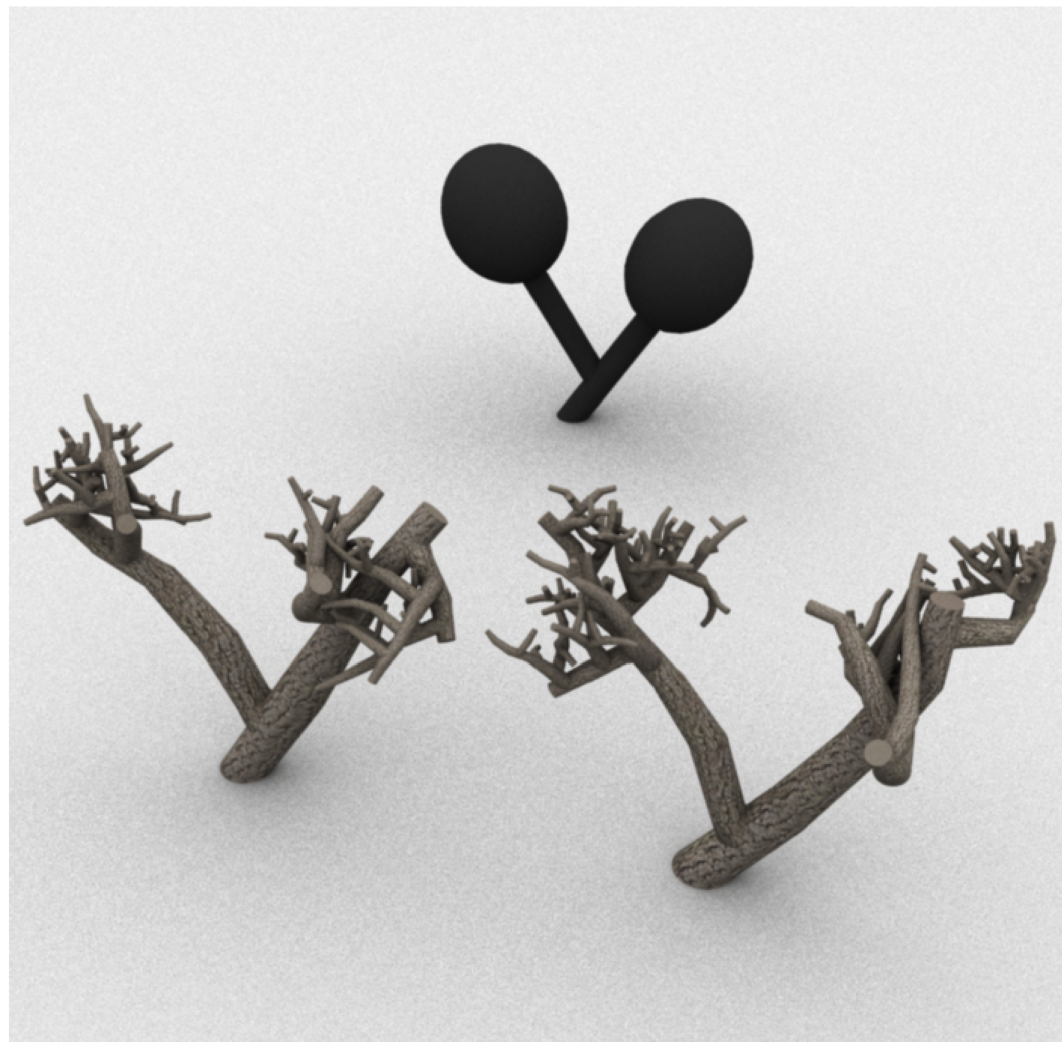
posterior inference



Kulkarni, Kohl, Tenenvaum, Mansinghka [CVPR'15]

Success story 3: Procedural modelling



Ritchie, Mildenhall, Goodman, Hanrahan [SIGGRAPH'15]

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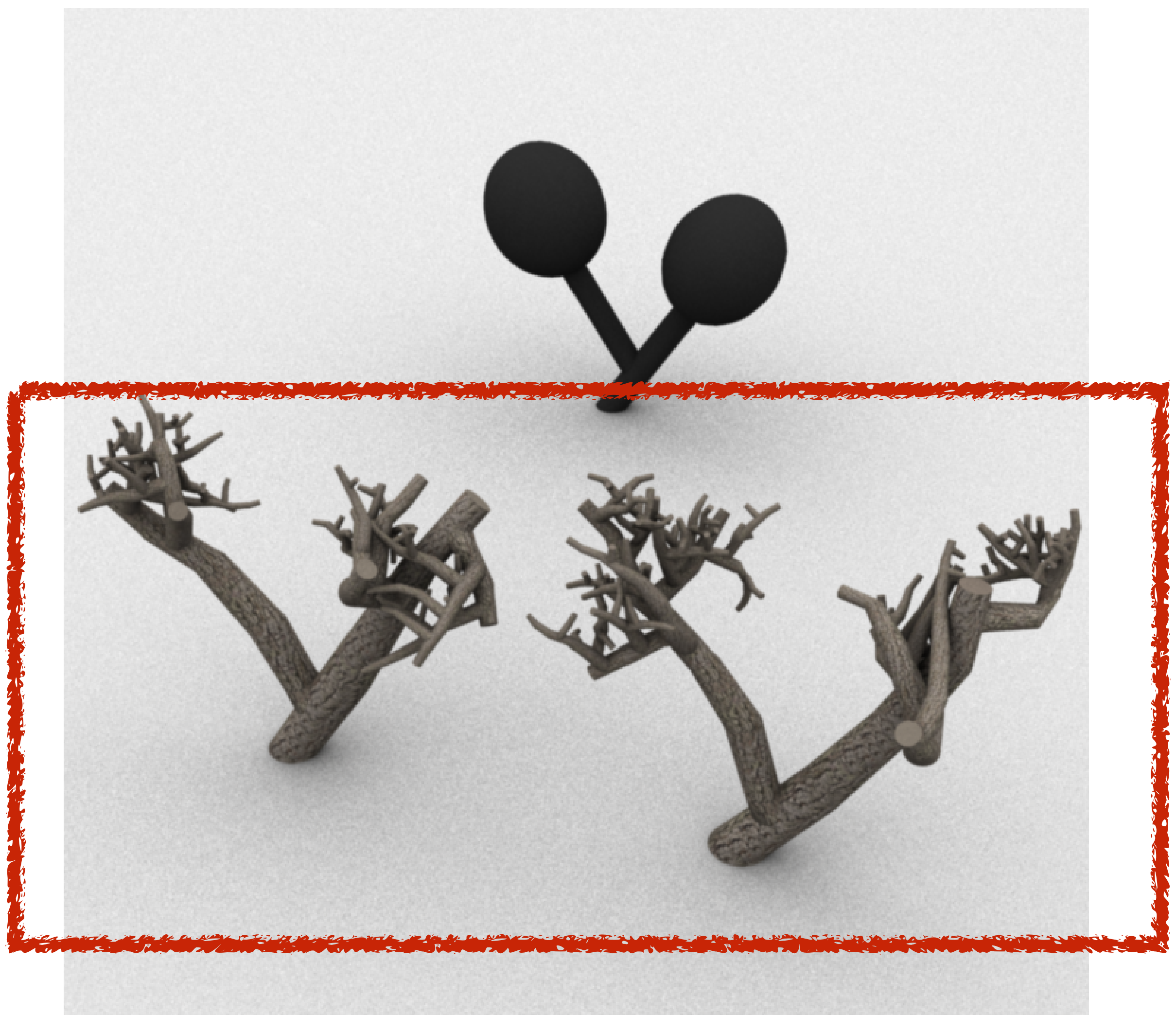
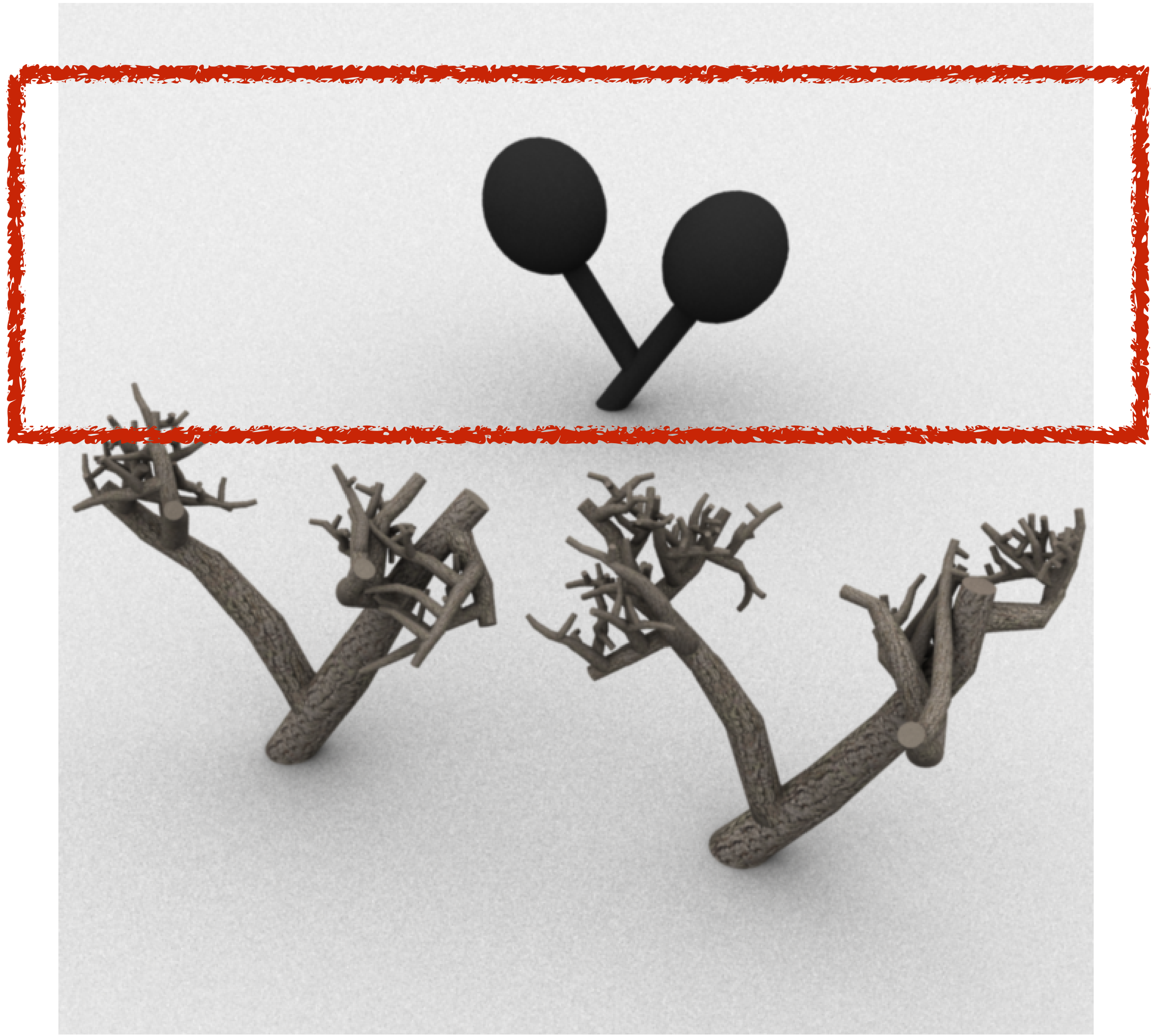


1. Sample a 3D object.

Ritchie, Mildenhall, Goodman, Hanrahan [SIGGRAPH'15]

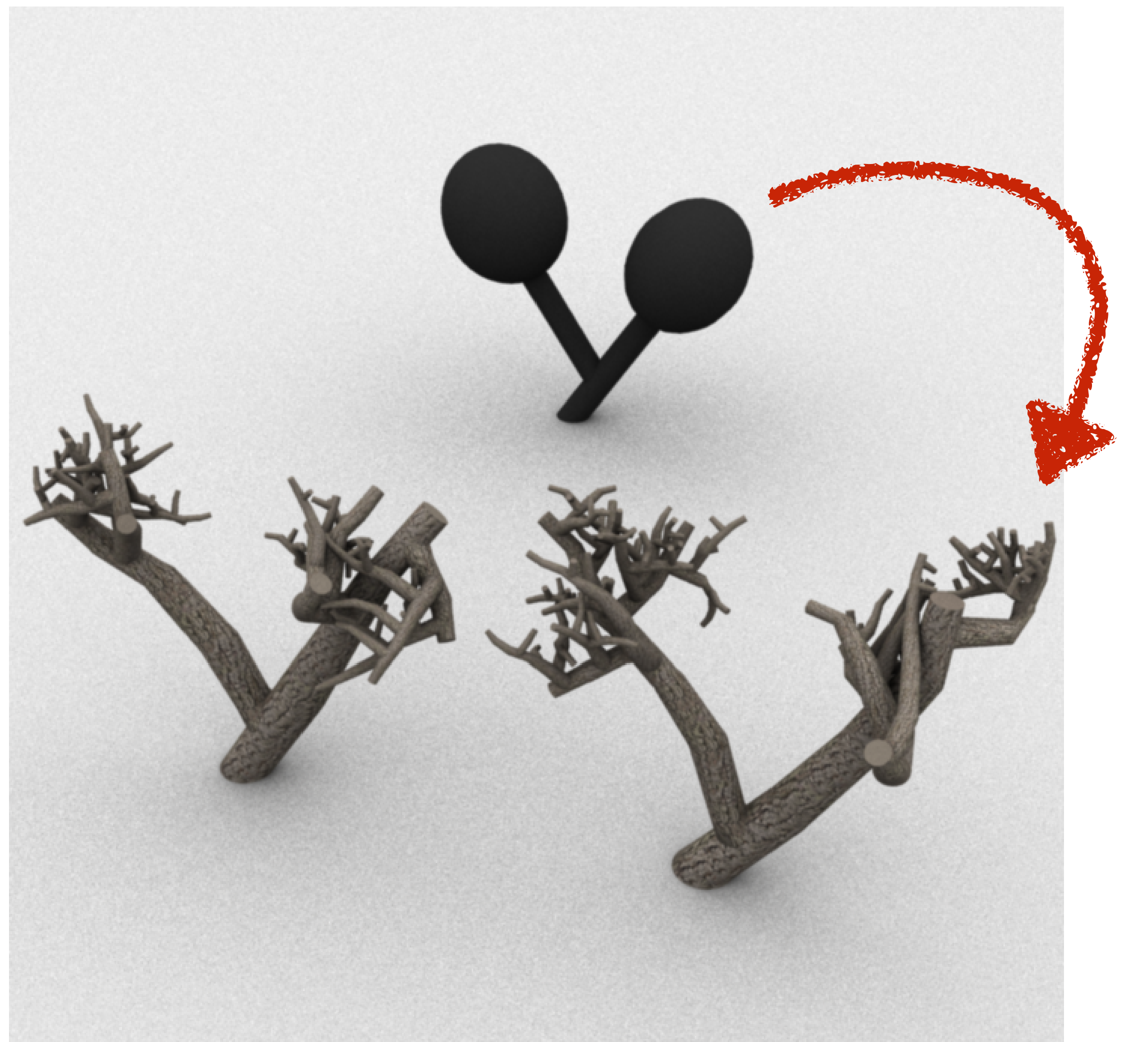
Success story 3: Procedural modelling



1. Sample a 3D object.
2. Score the object.

Ritchie, Mildenhall, Goodman, Hanrahan [SIGGRAPH'15]

Success story 3: Procedural modelling



1. Sample a 3D object.
2. Score the object.

Posterior inference generates objects with high scores.

Techniques used

- Changepoints: CPS transformation and new foundation of probability theory.
- Captcha and inverse graphics: neural nets and inference amortisation.
- Procedural modelling: sequential Monte Carlo algorithms and stochastic future.

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Prog. Languages, Machine Learning,

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Prog. Languages, Machine Learning, Probability Theory

Overview of the course

Objective

1. Learn how to write and reason about models in a prob. prog. language (PPL).
2. Learn results from ML/PL/prob. theory that are used for building effective PPLs.
3. Contribute to probabilistic programming.

Webpage

https://github.com/hongseok-yang/probprog17

All the important announcements will be made in this web page.

Evaluation

- 3-4 homework exercises (20%).
- Group project (40%).
- Final exam (40%).

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2-3 students form a group.

Two main tasks.

1. Presentation of a research paper or topic.
2. Project.
   - Track A: New cool application of a PPL.
   - Track B: Research on PPLs. ML/PL/math problems available in course webpage.

Announcement really important

1. Form a group and inform me and Byungsu by the midnight of Sep 11 (Monday).
2. Each group will meet me twice privately.
   (a) Sep 21-22 : Paper and topic selection.
   (b) Oct 26-27 : Progress check.
3. No lectures on Sep 4 and 6.

Announcement somewhat important

- Lecturer: Prof Hongseok Yang

  email: hongseok.yang@kaist.ac.kr

- TA: Byungsu Kim

  email: bskim90@kaist.ac.kr

- Install Anglican. Try the changepoint example. Get hints from the webpage.

Webpage

https://github.com/hongseok-yang/probprog17

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