Gaussian Material Synthesis

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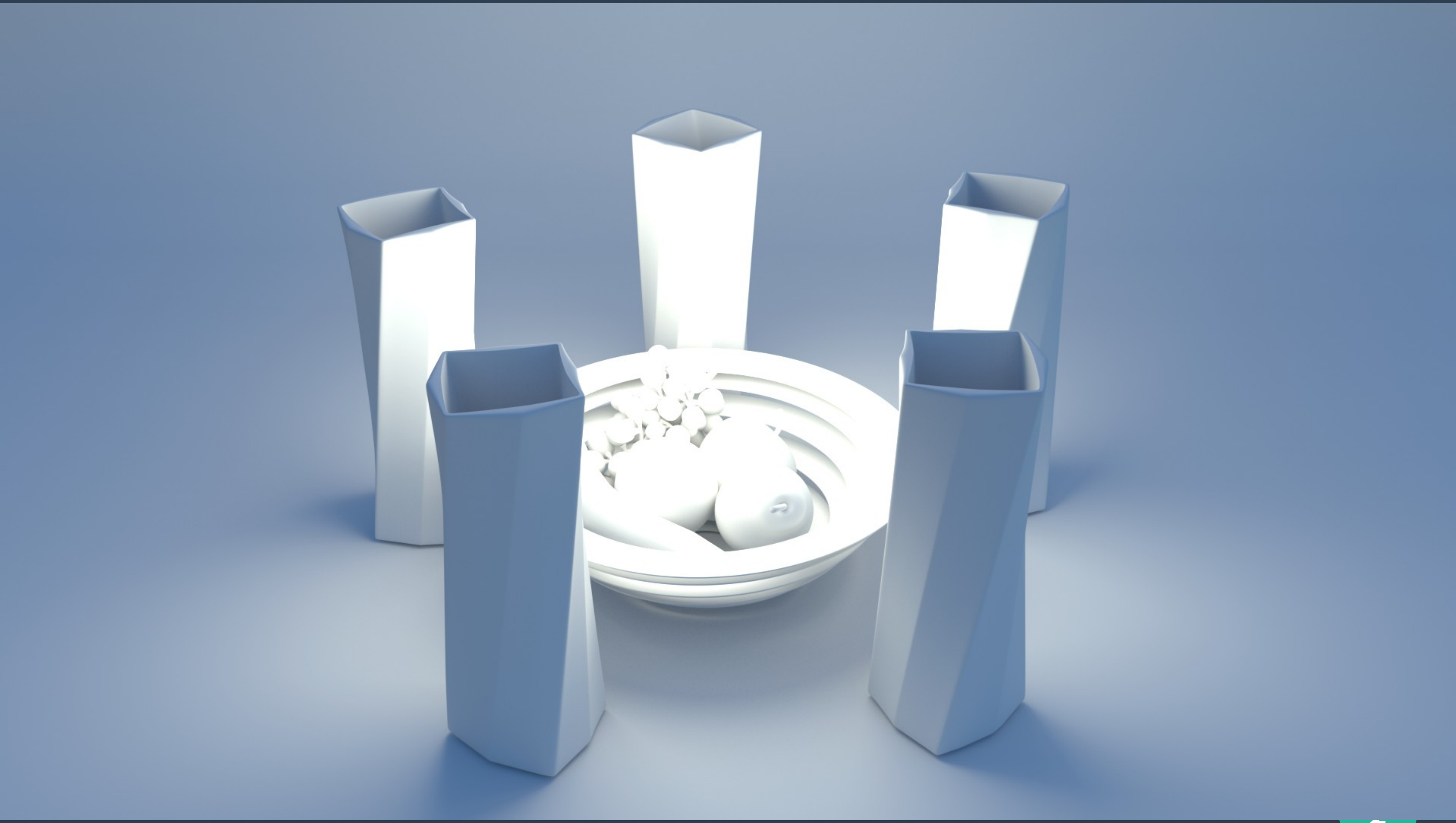
Ce propune acest articol?



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- **O metoda semi-automatizata de generare in masa de materiale in baza preferintelor unui utilizator**
- **De ce?**
  - Grafica tinde catre materiale fotorealiste (ray tracing)
  - Acestea sunt costisitor de creat
  - Necesita experti

Studii anterioare - Materiale

- **In trecut**
  - Se creau shadere pentru fiecare clasa de material
  - Nr mic de parametri configurabili
  - Limitat in expresivitate
  - Uneori se creau in baza pozelor

- **In prezent**
  - Popular este “principled shader” (Disney)
  - Nr mare de parametri
  - Cat mai expresiv

  “Uber-shader”

https://www.youtube.com/watch?v=6FzVhIV_t3s

Workflow

1) Invatarea preferintelor utilizatorului

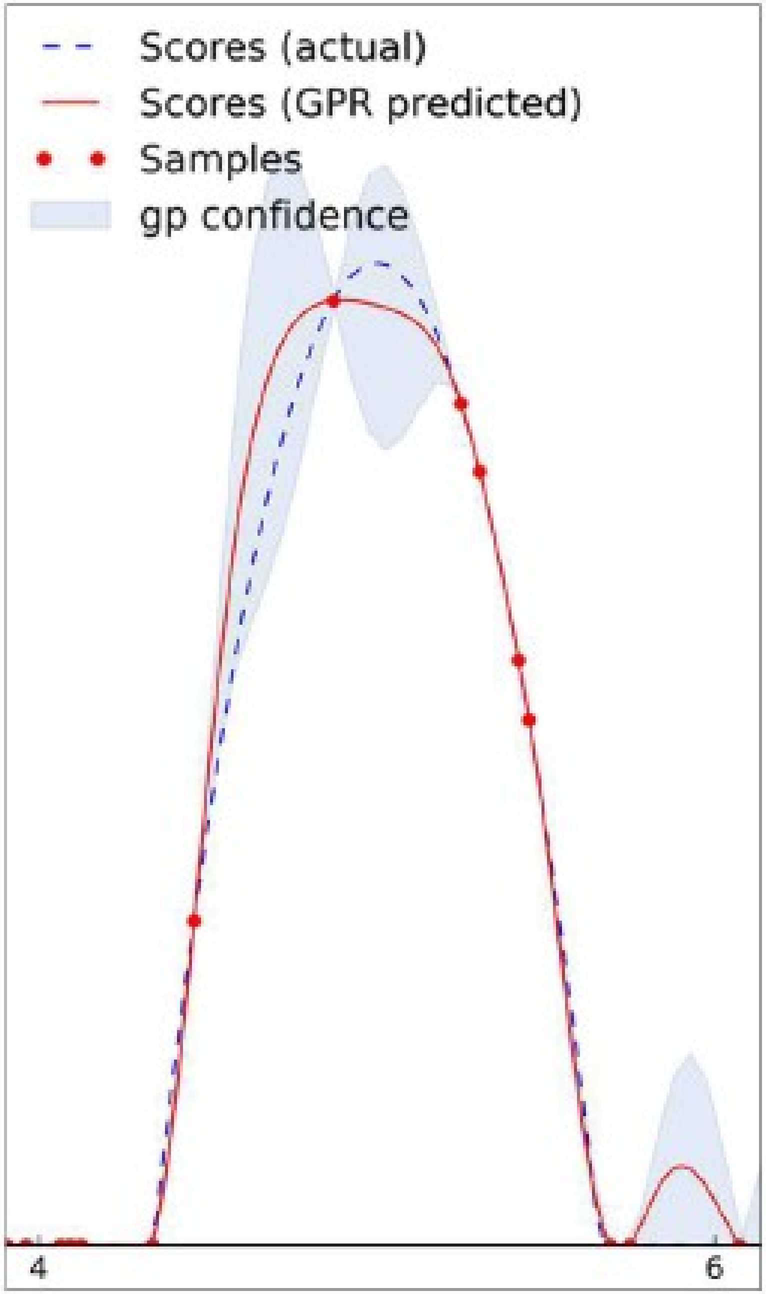
Gallery with scores

Gaussian Process Regression

- "kernel based Bayesian regression technique that leverages prior knowledge to perform high-quality regression from a low number of samples"

$$u(x),\ x \in R^m,\ m \in \{19, 38\}$$

$$U = [u(x_1), u(x_2), \ldots, u(x_n)]^T$$



Learning (GPR)

Gaussian Process Regression

- Functie de covarianta

$$k(\mathbf{x}, \mathbf{x}') = \sigma_f^2 \exp\left[-\frac{(\mathbf{x} - \mathbf{x}')^2}{2l^2} \right] + \beta^{-1}\delta_{xx'}, \qquad (1)$$

Pentru ||x – x’|| ~ 0 k tinde catre max

$$\theta = \{\sigma_f^2, l\}$$

Gaussian Process Regression

- Matricea de covarianta

$$\mathbf{K} = \begin{bmatrix} k(\mathbf{x}_1, \mathbf{x}_1) & k(\mathbf{x}_1, \mathbf{x}_2) & \dots & k(\mathbf{x}_1, \mathbf{x}_n) \\ k(\mathbf{x}_2, \mathbf{x}_1) & k(\mathbf{x}_2, \mathbf{x}_2) & \dots & k(\mathbf{x}_2, \mathbf{x}_n) \\ \vdots & \vdots & \ddots & \vdots \\ k(\mathbf{x}_n, \mathbf{x}_1) & k(\mathbf{x}_n, \mathbf{x}_2) & \dots & k(\mathbf{x}_n, \mathbf{x}_n) \end{bmatrix}, \tag{2}$$

- Cat de similare sunt intre ele materialele

Gaussian Process Regression

- Pentru un material generat x*

$$\mathbf{k}_* = \left[k(\mathbf{x}^*, x_1), k(\mathbf{x}^*, x_2), \ldots, k(\mathbf{x}^*, x_n)\right]^T, \tag{3}$$

Gaussian Process Regression

$$\begin{bmatrix} \mathbf{U} \\ u(\mathbf{x}^*) \end{bmatrix} \sim \mathcal{N}\left(0, \begin{bmatrix} \mathbf{K} & \mathbf{k}_*^T \\ \mathbf{k}_* & k_{**} \end{bmatrix}\right).$$

$$u(\mathbf{x}^*) = \mathbf{k}_*^T \mathbf{K}^{-1} \mathbf{U},$$

$$\sigma(u(\mathbf{x}^*)) = k_{**} - \mathbf{k}_* \mathbf{K}^{-1} \mathbf{k}_*^T.$$

Gaussian Process Regression

- Pentru invatarea lui θ se pot folosi algoritmi bazati pe optimizarea gradientului

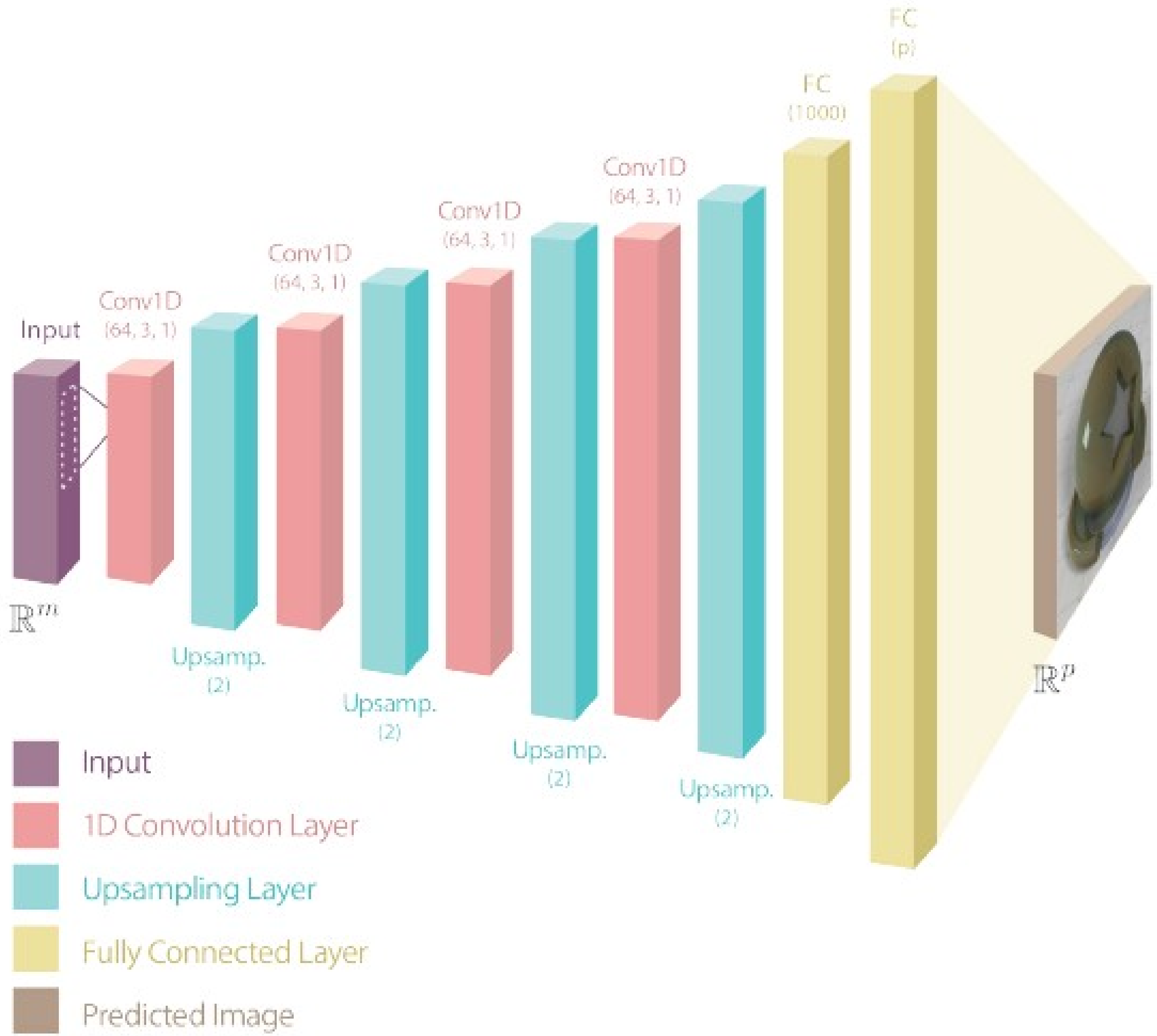
$$\log P\Big(\mathrm{U}|\mathbf{x},\theta\Big) = -\frac{1}{2}\mathrm{U}^T\mathbf{K}^{-1}\mathrm{U} - \frac{1}{2}\log|\mathbf{K}| - \frac{n}{2}\log 2\pi . \qquad (6)$$

$$\frac{\partial}{\partial\theta_j}\log P\Big(\mathrm{U}|\mathbf{x},\boldsymbol{\theta}\Big) = -\frac{1}{2}\operatorname{tr}\left\{\left(\boldsymbol{\alpha}\boldsymbol{\alpha}^T\mathbf{K}^{-1}\right)\frac{\partial\mathbf{K}}{\partial\theta_j}\right\},$$

Rendering

- Procesarea grafica a celor 300 de recomandari ar dura 4 ore
- 19/38 → $410^2 * 3$
- Geometria si iluminarea sunt constante

Gallery with scores



Input
$\mathbb{R}^m$
Conv1D
(64, 3, 1)
Upsamp.
(2)
Conv1D
(64, 3, 1)
Upsamp.
(2)
Conv1D
(64, 3, 1)
Upsamp.
(2)
Conv1D
(64, 3, 1)
Upsamp.
(2)
FC
(1000)
FC
(p)
$\mathbb{R}^p$
Input
1D Convolution Layer
Upsampling Layer
Fully Connected Layer
Predicted Image

Convolutional Neural Network

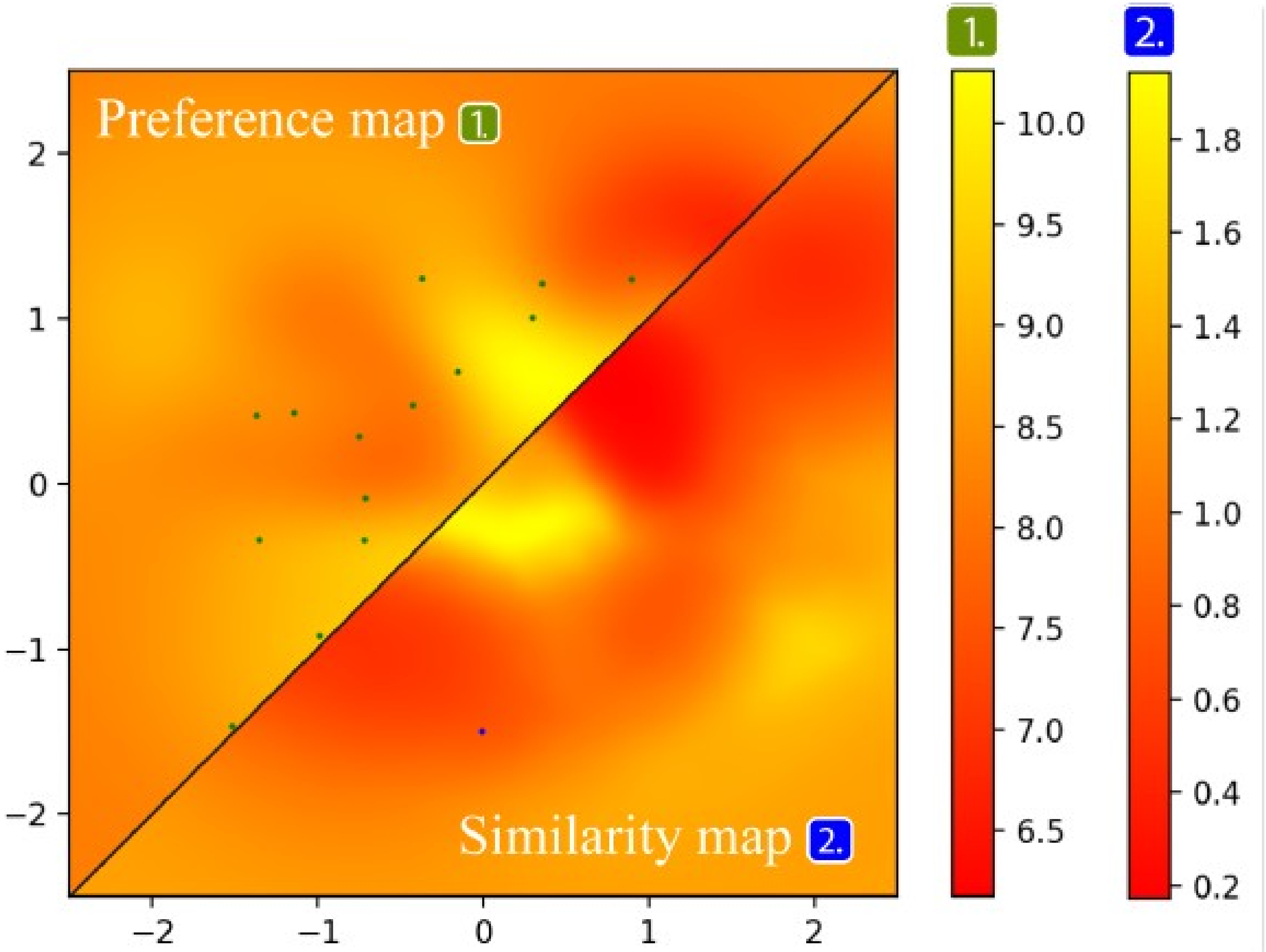
- **Avantaje**
  - Si-au generat setul de antrenare
  - Timpul de predictie: 3-4 ms
- **Numarul de straturi e ales sa nu invete zgomotul**
- **Dezavantaje**
  - Rularea este prohibitiva hardware

Fine-tuning

- Se doreste rafinarea unui material sugerat

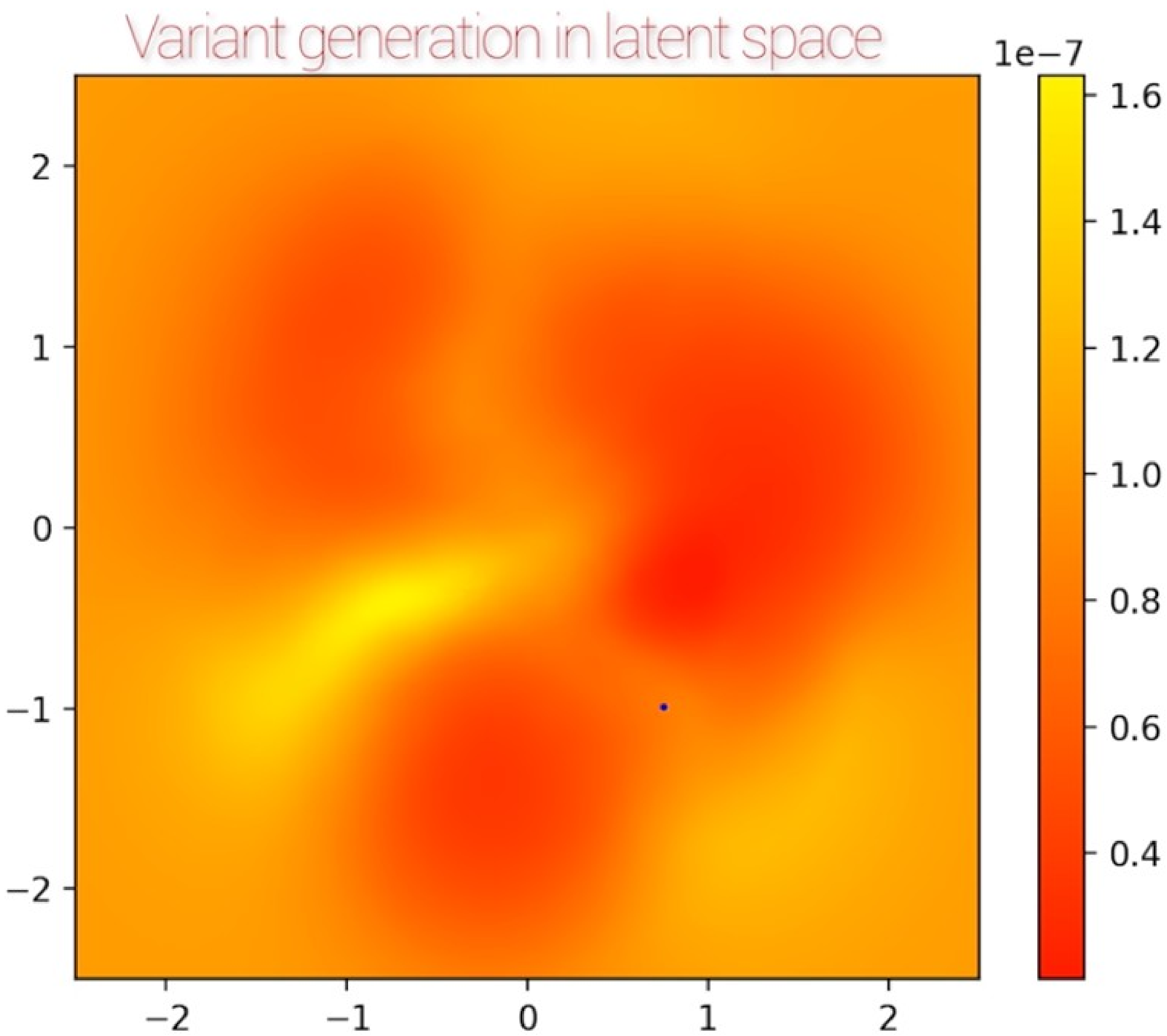
- Gaussian Process Latent Variable Model
- 19 → 2
- Transforma materiale in puncte 2D si interpoleaza in plan

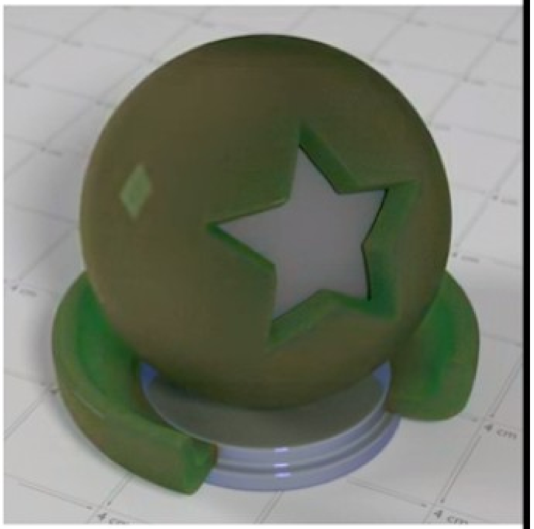
GPR + GPLVM



1.
2.
Preference map 1.
Similarity map 2.
2
1
0
−1
−2
−2
−1
0
1
2
10.0
9.5
9.0
8.5
8.0
7.5
7.0
6.5
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2

GPLVM + CNN (+ GPR)





Future work

- Adaptive learning
- Explorare mai agresiva a spatiilor generatoare de materiale
- “Two round recommandation”
- De la Imagini prezise la animatii
- Geometria si iluminarea sa nu mai fie constante

Multumesc!