Notes on Adversarial Machine Learning

1 Formalize Adversarial Attack

Explorative Attacks vs. Causative Attack

- **Explorative attacks**: the attacker influences only the evaluation data.
- > The attempts to passively circumvent the learning mechanism to explore blind spots in the learner
  >
  > ... to craft intrusions so as to evade the classifier without direct influence over the classifier itself
- **Causative attacks**: the attacker attempts to hack the training data as well.
- In the following survey, an adversary is usually assumed to be **explorative**.

Adversary's Goal

- For an input $I_c \in \mathbb{R}^m$, find a small perturbation ρ to force a classifier $\mathcal{C}$ to label ℓ. ((Szegedy et al. 2014)
- Another definition is to minimize the loss function on label ℓ, with perturbation ρ subject to some restriction.
  - **Targeted**: Fool the classifier to a specific label ℓ
  - **Untargeted**: Any ℓ different from the origin class suffices.

Adversary's Strength

- An adversary may have access to some of the knowledges below:
  - Training dataset
  - The feature representation of a sample (a vector in the feature space)
  - Learning algorithm of the model (e.g. architecture of a neural network)
  - The whole trained model with parameters
  - Output of the learner
- If an attack only requires input-output behavior of the model, it is referred to as a **black box attack**. (In some looser definition, the output of loss function is also accessible.)
- Otherwise, it is a **white box attack**.

2 Typical Attacks for Classification

Box-constrained L-BFGS (Szegedy et al. 2014)

- The origin goal (1) of an adversary is generally too hard a problem for optimization. It is helpful to transform it into the following form:

- We need to find the minimal parameter $c > 0$, such that $\mathcal{C}(I_c + \rho_c^*) = \ell$. The optimum of problem (3) can be sought using L-BFGS. It is proved that two optimization problem (1) and (3) yield same results under convex losses.
- Szegedy's paper also suggests an upper bound on unstability only by network architecture. This is done by inspecting the upper Lipschitz constant of each layer: if layer k is L_k-Lipschitz, the whole network would be $L = \prod_{k=1}^{K} L_k$ Lipschitz:

- This bound is usually too loose to be meaningful, but according to Szegedy, it implies that regularization that penalizing each upper Lipschitz bound might help the robustness of the network.

FGSM (Goodfellow et al. 2015)

- A **linear** and **one-shot** perturbation:
- In this paper, it is shown that:
  - Linear models are sufficient for the existence of adversarial attacks, since small perturbation results in a huge variation due to high dimensionality.
  - It is hypothesized that it is linearity instead of non-linearity that makes models vulnerable.
- The computational efficiency of one-shot perturbation enables adversarial training.

Iterative Methods (Kurakin et al. 2017)

- Basic iterative method: this is essentially a PGD of ℓ^∞ ball.
- Least-likely-class iterative method:
- where ℓ_{target} is the least likely class of prediction.

Jacobian based Saliency Map Attack

- ℓ_0 norm attack (not read yet)

One Pixel Attack

- Applies **differential evolution** to generate adversarial examples
- Black box attack: Requires only the predicted likelihood vector, but not the loss function or its gradient.

Carlini and Wagner Attacks

- Find objective functions f, such that

  which enables an alternative optimization formulation:
- An efficient objective function f is found to be

  where the classifier is assumed to be:

  The parameter $\kappa \geq 0$ forces an adversary to find adversarial examples of higher confidence. It is shown that κ is positively correlated to the transferability of the adversarial examples found.
- Yet another trick is used for the box constraints. Let $x = \frac{1}{2}(\tanh(w) + 1)$, so x satisfies $x \in [0, 1]$ automatically.

3 Transferability

- **Transferability:** the ability of an adversarial example to remain effective on differently trained models.
- A more careful definition (Papernot et al. 2016):
  - **Intra-technique** transferability: consider models trained with the same technique but different parameter

initializations or datasets
    - **cross-technique** transferability: consider models trained with different techniques
- Transferability empowers black-box attacks: to train a substitute model by querying the classifier as an oracle.
- Several methods for data augmentation are proposed by Papernot et al.

Universal Adversarial Perturbations (Moosavi-Dezfooli et al. 2017)

- A perturbation is **universal** if:

> For each image x in the validation set, we compute the adversarial perturbation vector $r(x)$ ... To quantify the correlation between different regions of the decision boundary of the classifier, we define the matrix $N = [\frac{r(x_1)}{\|r(x_1)\|_2} \cdots \frac{r(x_n)}{\|r(x_n)\|_2}]$

- The author compares the singular values of matrix N with the singular values of a matrix with columns sampled randomly.
- It is explained that a subspace of dimension $d' \ll d$ containing most normal vectors to the decision boundary in regions
surrounding natural images.

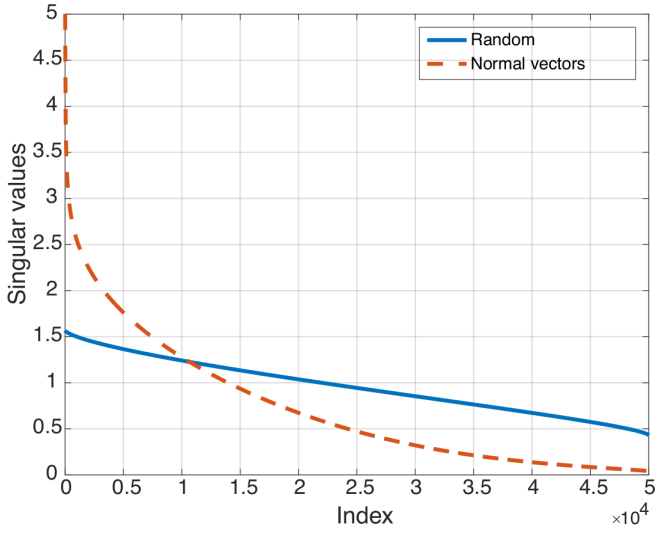


Figure 9: Singular values of matrix N containing normal vectors to the decision decision boundary.

Myth:

- Why adversarial examples are so close to any input x?
- Why adversarial examples looks like random noise?
- Why training with mislabeling also yields models with great performance?
- I listened to an online report made by **Adi Shamir**
- Assumptions:
    - k-manifold assumption
    - The boundary of a classification network is only pushed to get close to the manifold during training
    - Claim: adversarial examples are nearly orthogonal to the manifold.
    - Test using generative model!

4 Defenses

1. Adversarial Training

- Intuition: to argument the training data with perturbated examples.
- Solving the min-max problem

2. To Detect Adversarial Examples

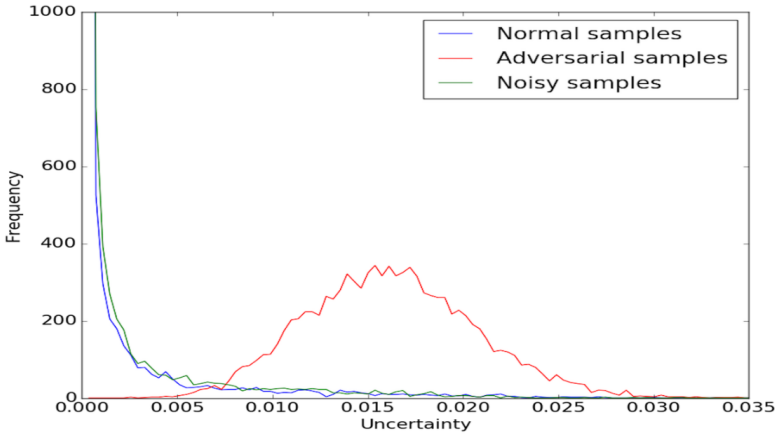
On Detecting Adversarial Perturbations (Metzen et al. 2017)

- Intuition: to train a small subnetwork for distinguishing genuine data from data containing adversarial perturbation
- Train a normal classifier ⇒ Generate adversarial examples ⇒ Train the detector
- Worst case: the adversary adapts to the detector:

- where σ allows the dynamic adversary to trade off these two objectives.
- Apply the dynamic adversary and the detector alternately.

Detecting Adversarial Samples from Artifacts (Feinman et al. 2017)

- A crucial drawback of Metzen's work: must be trained on generated adversarial examples
- An intuition: high dimensional datasets are believed to lie on a low-dim manifold; and the adversarial perturbations must push samples off the data manifold.
- **Kernel Density estimation:** Detect the points that are far away from the manifold.
  - where X_t is the set of training data with label t (here t means the predicted class).
  - $k(\cdot, \cdot)$ is the kernel function and $\phi(\cdot)$ maps input x to its feature vector of the last hidden layer.
  - Another intuition: deeper layers provide more linear and unwrapped manifold.
- **Bayesian Neural Network Uncertainty:** identify low-confidence regions by capturing "variance" of predictions
  - Randomness is considered under dropouts and parameters are sampled for T times.
  - where $y^* = f(x^*)$ is a prediction of test input $x*$.
  - It is shown that typical adversarial examples do have much different distributions on uncertainty.



(a) BIM

Adversarial Examples Are Not Easily Detected: Bypassing Ten Detection Methods (Carlini et al. 2017)

- Analyze 10 proposed defenses to detect adversarial examples
- Conclusion: all these defenses are *inefficient* when an adversary is aware the neural network is being secured with a given detection scheme; and some of the properties claimed for adversarial examples are only due to existing attack techniques.
- The 10 defenses can be categorized:
    1. Train a secondary neural network for detection
    2. Capture statistical properties
    3. Perform input-normalization with randomization and blurring
- Break each defenses by:
    1. Secondary Detector:
        - Treat "malicious" as a new label. Combine the detector and the classifier:

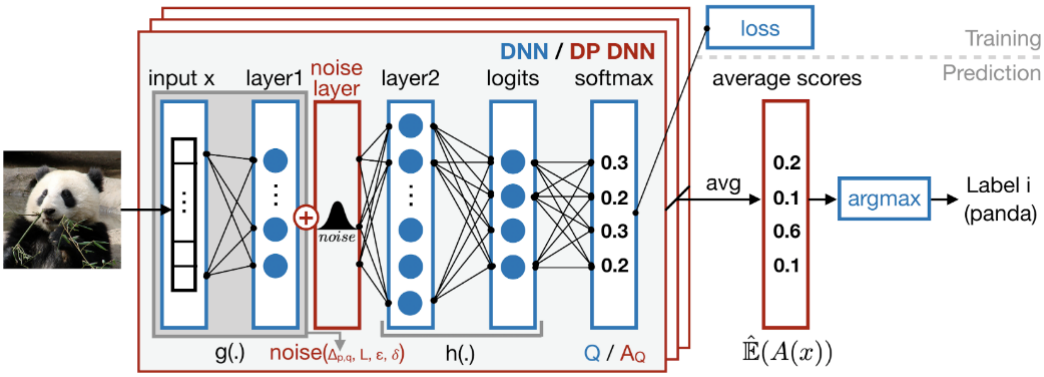
      where Z_F, Z_D are logits of the classifier and detector, respectively.
        - The detector marks "malicious" $\Leftrightarrow Z_D(x) > 0 \Leftrightarrow \arg\max_i G(x_i) = N+1$
    2.

3. Certified Defenses

> Aim to "provide rigorous guarantees of robustness against norm-bounded attacks"

Certified Robustness to Adversarial Examples with Differential Privacy (Lecuyer et al. 2019)

- Consider a classifier $\mathcal{C}(x)$ that outputs soft labels $(p_1, \ldots, p_n)$, $\sum_{i=1}^n p_i = 1$.
- Suppose $\mathcal{C}(x)$ is (ϵ, δ)-DP, which implies $\mathbb{E}[p_i(x)] = e^\epsilon \mathbb{E}[p_i(x')] + \delta$, for any x, x' such that $d(x, x') < 1$.
- **Main theorem:** If $\mathcal{C}$ is (ϵ, δ)-DP, w.r.t. ℓ_p norm, and $\forall x, \exists k$, s.t.:
    -
    - Then the classification model $y = \arg\max_{i=1}^n p_i$ is robust to attacks within the ℓ_p unit ball.
- This is different from traditional DP which uses ℓ_0 norm for $d(x, x')$, and the definition of sensitivity must also be changed:
- The conclusion of DP can be applied to p norm as well, namely: Laplacian mechanism works for bounded $\Delta_{p,1}$ and Gaussian mechanism works for $\Delta_{p,2}$. Moreover, as DP is immune to post-processing, we can add these noises at layer of the network!
- Overall Scheme: Pre-noise layers + noise layer $\longrightarrow$ Post-noise layers
- Only need to bound the sensitivity of pre-noise computation $x \mapsto g(x)$. This is done by transforming g to $\tilde{g}$ with $\Delta_{p,q}^{(\tilde{g})} \leq 1$.
    - Techniques: Normalization, Projection SGD (Parseval networks, tbd).

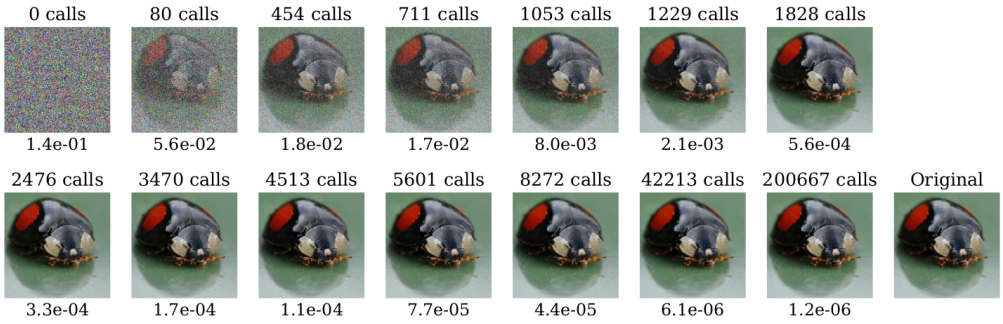


(a) PixelDP DNN Architecture

5 Restricted Threat Model Attacks

Decision-Based Adversarial Attacks: Reliable Attacks Against Black-Box Machine Learning Models

- Story so far: gradient-based, score-based and transfer-based attacks
- > Definition **(Decision-based attacks):** Direct attacks that solely rely on the final decision of the model
- **Method:** Initialize with an adversarial input $x_0 = x'$, make random walk according to a "proposal distribution", trying to reduce $||x_k - x^*||$.
- **Performance:** Requires (unsurprisingly) much more iterations of forward passes.



6 Generative Models

6.1 Variational Autoencoder (VAE) Background

- latent representation $z = Enc(x)$, and decoder/generator maps z to $\hat{x}$. $\hat{x} = Dec(z)$.
- VAE aims to learn a latent representation for posterior distribution $p(z|x)$. Maximize loss function (minimize KL divergence):

7 Verifiably Robust Models

7.1 Interval Bound Propagation

- For input x_0 and logits x_k, we want worst case robustness in a neighbour of x_0:
- where $z_k = logits(z_0)$.
- Consider $z_k = \sigma(h(z_{k-1}))$ with monotonic activation function σ, $\overline{z}_k = h(\overline{z}_{k-1})$ and $\underline{z}_k = h(\underline{z}_{k-1})$.
- Let $\overline{z}_0(\epsilon) = z_0 + \epsilon\mathbf{1}$ and $\underline{z}_0(\epsilon) = z_0 - \epsilon\mathbf{1}$.
- Left hand size of ??? is bounded by $\overline{z}_{k,y}(\epsilon) - \underline{z}_{k,true}(\epsilon)$. To minimuze this term, define:
- Then minimize hybrid training loss:

8 Physical World Attacks

Synthesizing Robust Adversarial Examples

Expectation Over Transformation

- To address the issue: adversarial examples does not keep adversarial under image transformations in the real world.
- Minimize visual difference $t(x) - t(x')$ instead of $x - x'$ in texture space
- The distribution T of transformations:
  - 2D: $t(x) = Ax + b$
  - 3D: texture x, render it on an object to $Mx + b$
- Optimize the objective:

Fooling Automated Surveillance Cameras Adversarial Patches to Attack Person Detection

- Patch Adversarial Attack: only structurally editing certain local areas on an image
- A pipeline of **patch attack**

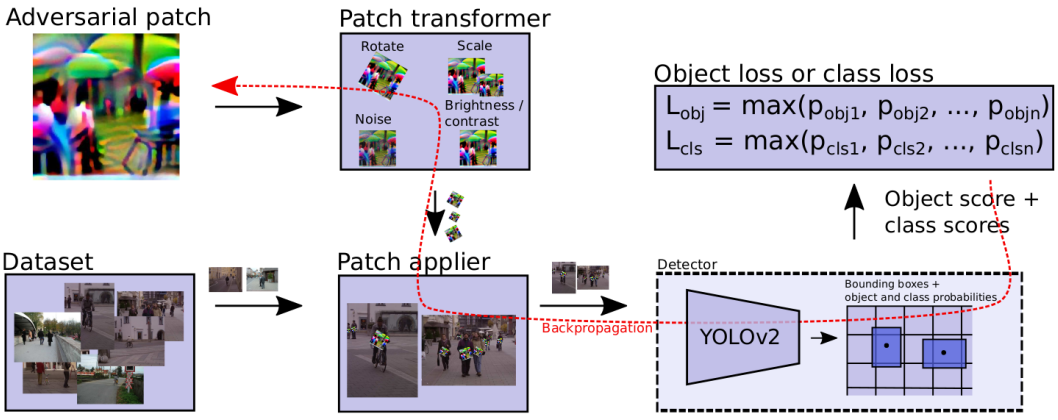


Figure 3: Overview of the pipeline to get the object loss.

- Hybrid Objectives:
  - L_{nps} non-printability score
  - L_{tv} the total variation loss. Force the image to be smooth.
  - L_{obj} maximize the objectness $p(obj)$. Note that we can also use L_{cls} (class score) or both.

Adversarial T-shirt! Evading Person Detectors in A Physical World

Thin Plate Spline (TPS) mapping

- To learn transformations t that maps each pixel $p^{(x)}$ to $p^{(z)}$.
- Suppose $p^{(x)} = (\phi^{(x)}, \psi^{(x)})$, $p^{(z)} = (\phi^{(x)} + \Delta_\phi, \psi^{(x)} + \Delta_\psi)$.
- According to TPS method, the only solution of Δ is given by:

  where the radial basis function $U(r) = r^2 \log r$ and $\hat{p}_i^{(x)}$ are n sampled points on image x.
- TPS resorts to a regression problem to determine θ, in which the regression objective is to minimize the difference between
- This results in an equivalent problem:

  where $K_{ij} = U(\|\hat{p}_i^{(x)} - \hat{p}_j^{(x)}\|)$ $\theta_\phi = [c, a]$ and $P = [1, \hat{\phi}^{(x)}, \hat{\psi}^{(x)}]$.

  (See Code for TPS for implementing details.)

Adversarial T-shirts generation

- The pipeline is similar as above. The major difference is the composited transformation adopted here.
- The overall transformation is given by:

- $A = (1 - M_{p,i}) \circ x_i$ yields the background region, $B = M_{p,i} \circ x_i$ is the human-bounded region.
- $C = M_{c,i} \circ x_i$ is the bounding box of T-shirt.
- t_{color} is applied in place of non-printability loss.
- t stands for conventional physical transformations, t_{env} for brightness of the whole environment.
- Gaussian smoothing is applied by v to the adversarial patch.

Can 3D Adversarial Logos Cloak Humans?

- Various postures and multi-view transformations threatens the adversarial property of previous 2D adversarial patches
- Overall pipeline: Detach 3D logos from person mesh as submeshes $\mathcal{L}$, then:
  - Texture $\mathcal{S}$
  - $\mathcal{M}_{2D}$ maps a 3D logo to 2D domain $[0, 1]^2$; M_{3D} attach texture to 3D logo

  Finally, render the 3D adv logo by differentiable renderer (e.g. Neural 3D Mesh Renderer) with human and background.
- **Loss**

- DIS: disappearance loss = the maximum confidence of all bounding boxes that contain the target object
- TV: total variance: $TV(\tilde{\mathcal{L}}) = \sum_{i,j}(|R(\tilde{\mathcal{L}})_{i,j} - R(\tilde{\mathcal{L}})_{i,j+1}| + |R(\tilde{\mathcal{L}})_{i+1,j} - R(\tilde{\mathcal{L}})_{i,j}|)$ captures discontinuity of 2D adv logo. (Here R stands for rendering.)

Adversarial Texture for Fooling Person Detectors in Physical World

- > Goal: to train an expandable texture that can cover any clothes in any size

- Four methods: RCA, TCA, EGA, TC-EGA
- Code Notes

9 Object Detection

9.1 YOLO

- $S \times S$ grids, each containing B anchor points with bounding boxes
- Each anchor point: $[x, y, w, h, p_{obj}, p_{\ell 1}, \ldots, p_{\ell n}]$
- p_{obj}: object probability. The prob. of containing an object.
- $p_{\ell i}$: Class score, learned by SoftMax and cross entropy
- Confidence of object: measured by $p_{obj} \times IOU$.
- Confidence of class: measured by $p_{obj} \times IOU \times \Pr[\ell_i \mid obj]$
- Yolo: Outputs [`batch`, `num_class` + 5$\times$`num_anchors`, $H \times W$]
- Yolov2: Outputs [`batch`, (`num_class` + 5)$\times$`num_anchors`, $H \times W$] (See details at below).

9.2 Region proposal network

- CNN generates anchors:
  - For each pixel on the feature map (say 256 dimension with size H$\times W$), generate $k = 9$ anchors.
  - The height-weight ratio of these 9 anchors are 0.5, 1 or 2, each with three different size.
  - Each pixel has $2k$ scores and $4k$ coordinates. Each anchor yields a foreground and a background score. Use softmax to decide where it is foreground or background.
- Meanwhile, use **bounding box regression** on each anchor. (Another branch)
- Finally, **Proposal Layer** takes sum over anchors and BBox regression.
  - Sort these anchors by foreground softmax scores.
  - Delete anchors that surpass too much from boundary.
  - Use **Non-maximum suppression** to avoid multiple anchors on a single object. (Recursively choose the anchor with highest score and delete other anchors with high IOU against it.)

9.3 Bounding Box

- Original bounding box $P(x, y, w, h)$, learn deformation $d(P)$ to approximate the ground truth
- where $d(P) = w^T \phi(P)$. ϕ is the feature vector so we shall learn parameter w

9.4 ROI Alignment

- The proposed anchors have different size (w, h), pool the corresponding feature map (with size $w/16, h/16$) to a fixed size (w_p, h_p). In each of these $w_p h_p$ grids, do max pooling.
- Finally, apply FC layers to calculate class probability and use bounding box regression again.

10 Basic Graphics

10.1 Coordinates

- World coordinates: (x, y, z) means left, up and in.
  - Azimuth: 经度角
- Camera Projection Matrix K (intrinsic parameters of a camera)
  - From 3D world (metric space) to 2D image (pixel space)
- Coordinate transformation from **world coordinate** $\mathbf{X}$ to **camera coordinate** $\mathbf{X}_c$:

10.2 Obj format

- vertex: 3D coordinate. In format: `v x y z`
- vertex texture: 2D coordinate in texture figure. In format: `vt x y`
- vertex normal: normal direction. In format: `vn x y z`
- face. In format: `f v1/vt1/vn1 v2/vt2/vn2 v3/vt3/vn3`.
- See examples here

10.3 Pytorch3d

- load an object
  - `verts, faces, aux = load_obj(obj_dir)`
  - OR `mesh = load_objs_as_meshes([obj_dir], device)`
- Mesh: Representations of vertices and faces
  - List | Padded | Packed
  - $[[v_1], \ldots, [v_n]]$ | has batch dimension | no batch dimension, index into padded representatoin
  - e.g. `vertex = mesh.verts_packed()`
- Mesh.textures:
  - Three possible representations:
    - TexturesAtlas (each face has a texture map)
      - (N,F,R,R,C): each face use $R \times R$ grid
    - TexturesUV: a UV map from vertices to texture image
    - TexturesVertex: a color for each vertex

```
#for uv:
mesh.textures.verts_uvs_padded()
#for TexturesVertex:
rgb_texture = torch.tensor([1,vertex.shape[0], 3]).uniform_(0,1)
mesh.textures = TexturesVertex(vertex_features = rgb_texture)
```

10.4 Render

- Luminous Flux: $dF = dE/(dS \cdot dt)$.
- Radiance: $I = dF/d\omega$. (立体角)
- Conservation:
  - $I_i = I_d + I_s + I_t + I_v$.
  - Diffuse light: $I_d = I_i K_d(\vec{L} \cdot \vec{N})$
    - where $\vec{L}$ is the orientation of the initial light and $\vec{N}$ is the normal orientation.
  - Specular light: $I_s = I_i K_s(\vec{R} \cdot \vec{V})^n$
    - where $\vec{R}$ is the reflective light and $\vec{V}$ is the direction of view.
  - Ambient light: $I_a = I_i K_a$.

- Shading
  - Gouraud: Color interpolation (barycentric interpolation)
  - Phong: Normal vector interpolation

11 Others

11.1 Entropy, KL divergence

- Entropy $H(X) = -\sum_{x\in X} p(x)\log p(x)$.
- Cross entropy $XE(p,q) = \mathbb{E}_p(-\log q)$.
- The distance between two distributions p and q can be measured by:

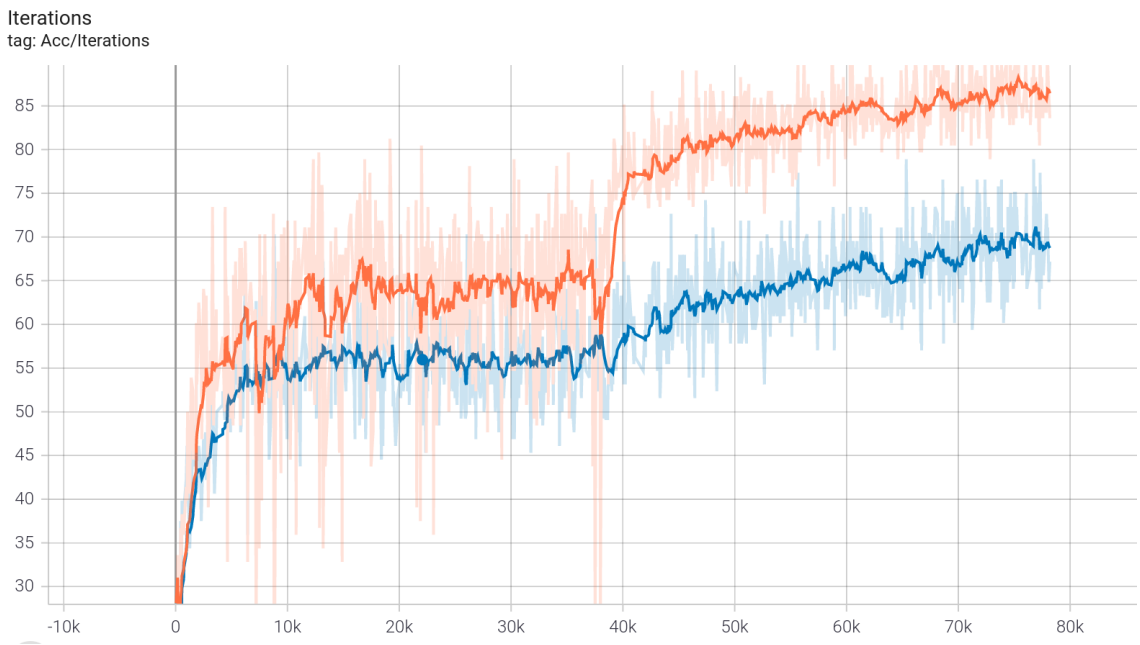
  which represents the information loss of describing $p(x)$ by $q(x)$.
- Mutual Information: $\mathbb{I}(X;Y) = KL(p(X,Y)|p(X)p(Y))$.

11.2 Statistics

- Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$
- Precision = $\frac{TP}{TP+FP}$
- Recall = $\frac{TP}{TP+FN}$
- PR-curve: traverses all outoffs to get a tradeoff curve of precision and recall

12 Experiments

- FGSM, BIM, Carlini & Wagner attacks
- Adversarial Training
  - FGSM adversarial training



	Accuracy	FGSM ($e = 4/255$)	CW ($e = 4/255, a = 0.01, K = 10$)
75999.pth	0.817	0.6634	0.099

- Adversarial Texture:
  - TCA-1000epoch: AP = 0.6395
  - TCEGA-2000,1000: AP = 0.4472

- TCEGA-HSV-red-2000,1000: AP = 0.6951
- TCEGA-Gaussian-2000,1000: AP = 0.4916

Pytorch3d Experiments

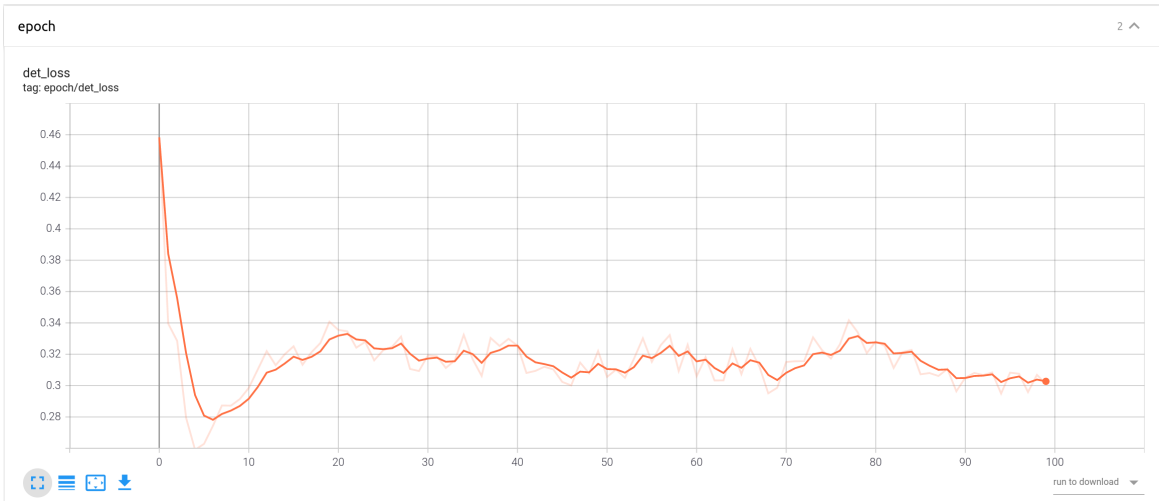
Adv_3d

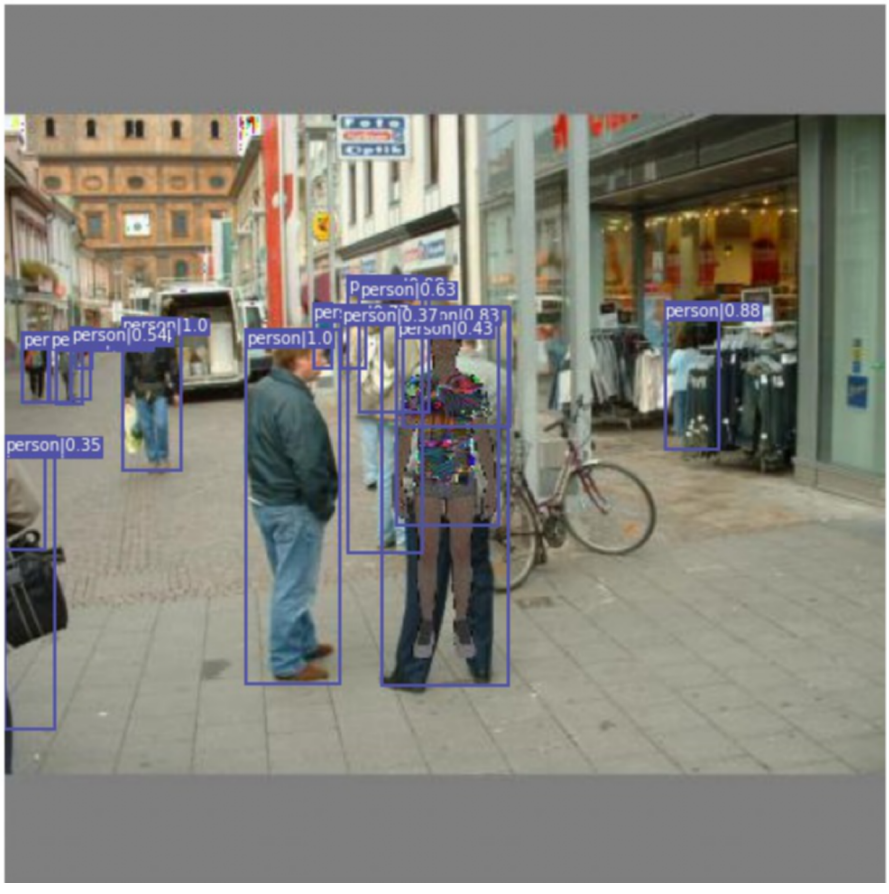
- Differentiable Rendering + original adv_patch pipeline
- MaxProbExtractor: Only optimize the box with max iou!

Issues:

- Parrallel
  - solved by modifying detection/transfer.py
  - may introduce problems of space redundancy
  - Config now: batch size = 2, num_views = 4, any bigger batch size causes cuda out of memory
  - 10 minutes/batch
- Project a [3,H,W] cloth to TextureAtlas
  - try TextureUV, but the projection from texture.jpg to TextureUV seems not differentiable
- Add more constraints?
- Ensemble learning

Experiment1: Batch: 2×4, lr = 0.001, attack faster-rcnn



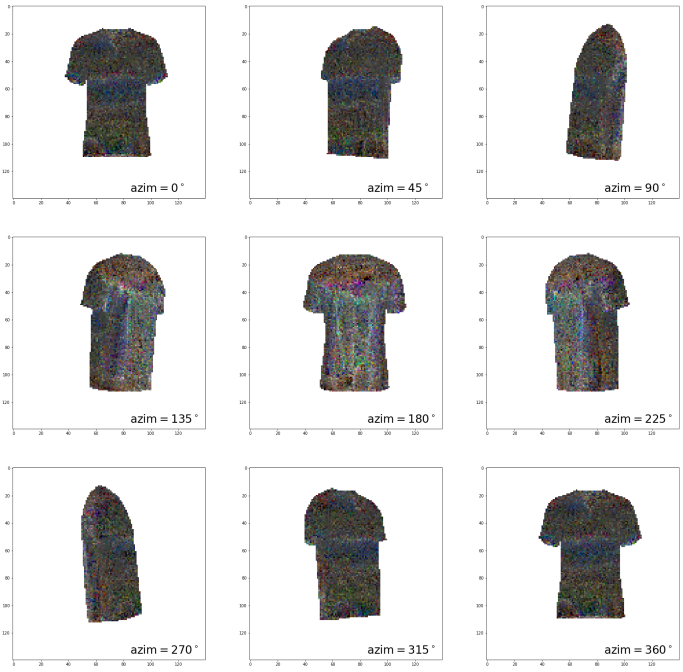


- The tendency of attacking two-stage detectors such as faster-rcnn: split boxes to smaller ones

- MaxProbExtractor: Only to attack the box with max iou may sacrifice those boxes with smaller iou but much higher probability? (**Failed**, the current method works great enough)
    - now: iou threshold 0.4, prevent over-optimizing on trivial boxes.
    - try attacking the box with max confidence = iou $\times$ prob?
- We now take the mean of gradient over B pictures. Why not try weighted mean (e.g. ℓ_2) or other loss functions (e.g. $\sum e^{prob}$) to urge the trainer to attack the largest max_prob boxes?
- Model placed in the middle of the picture (Overfit?) (Usually **not** a problem here)

- 8.28: I observe that over the parameters in the shape of [1,6906,8,8,3], only 3.49% of them (46333) deviate from original setup 0.5 (for grey). Over the trained parameters, 18.7% of them go beyond the [0,1] range.
- 8.31 I render the patch trained by 4 viewing points (0,90,180,270), it turns out that a small deviation from these angles would make the rendered picture almost completely grey:
    - It turns out that this is due to the Atlas expression of texture

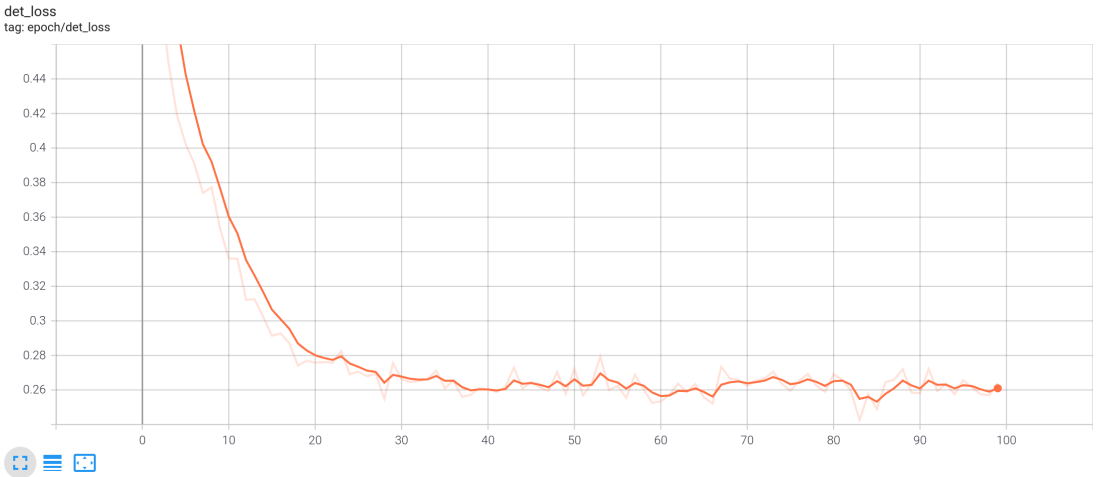
- 8.31 I try 50% droppout on the adv patch (a random 0/1 mask of size 6000):
    - 100%: recall = 0.10, 80%: recall = 0.32, 50%: recall = 0.89. **(fail)**
- 9.1 experiment4: random angles (163937) **(fail)**
    - parameters 87.59% trained
    - 没有形成完整连续的图像，几乎没有对抗效果 (recall = 0.96)，但loss一直在0.3上下
    - I fixed the viewing angles for each epoch, so perhaps the tshirt is trained only adversarial for those views at end of each epoch. (**fixed later in experiment 7**)



- 9.4 experiment5: vec2atlas, R = 8. (Map $(3, V)$ to atlas $(1, V, R, R, 3)$ before the previous pipeline).
    - recall = 0.20
- 9.3 experiment6: vec2atlas, R=2.
    - Reducing parameter R does not influence the quality of the rendered pics much, but save memory and time.

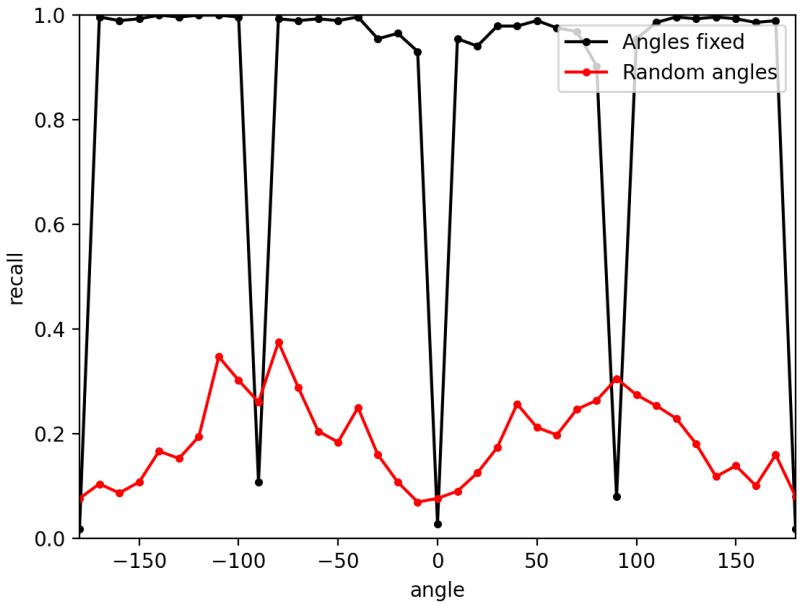
from $(3, V)$ to $(1, V, R, R, 3), R = 2$,recall=0.20

- it seems that R=8 introduces too much parameters for a normal tshirt
- experiment7: R=2, random angle, switch every 20 iterations, vec2atlas



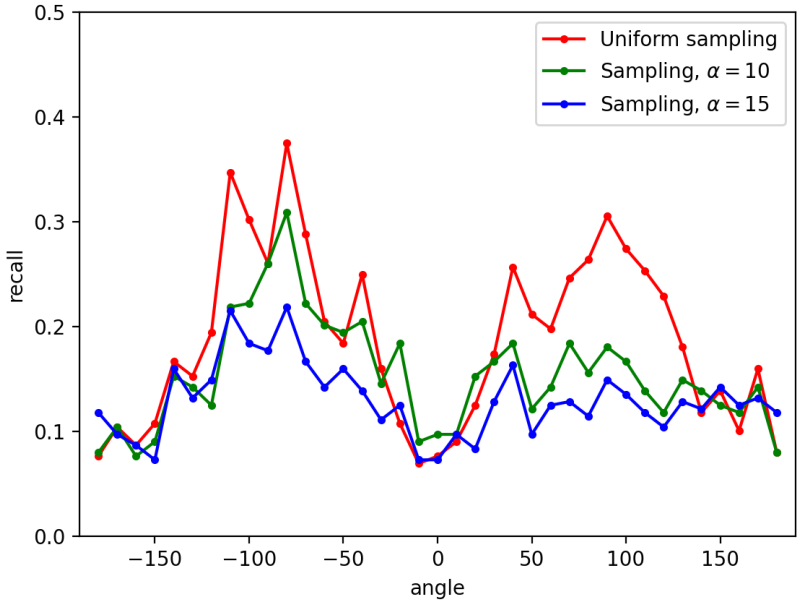
Loss curve for random angle sampling

  - It turns out that random sampling takes about three times the epoches to converge as using fixed angles, but the figure below demonstrates the failure of the latter option on universal angles.

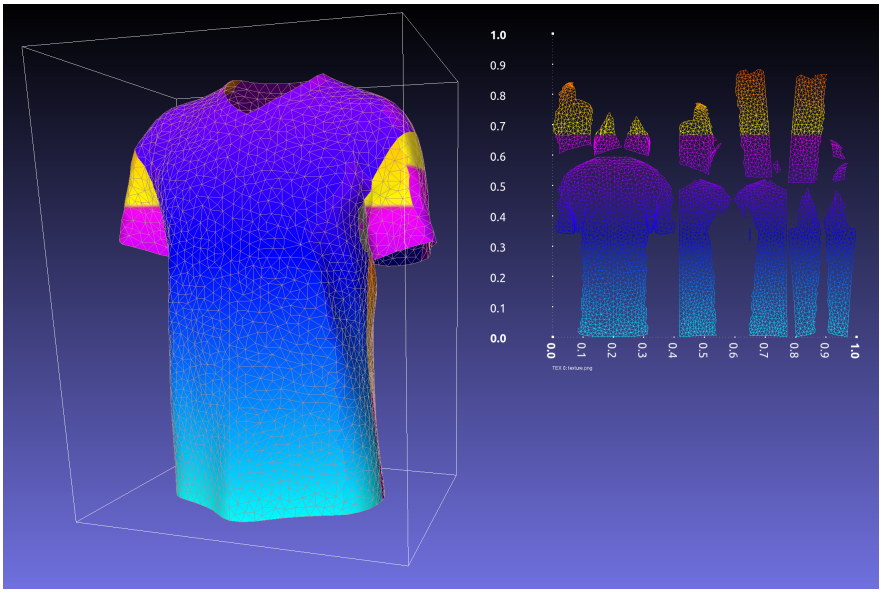


conf_thresh = 0.01, iou_thresh = 0.5

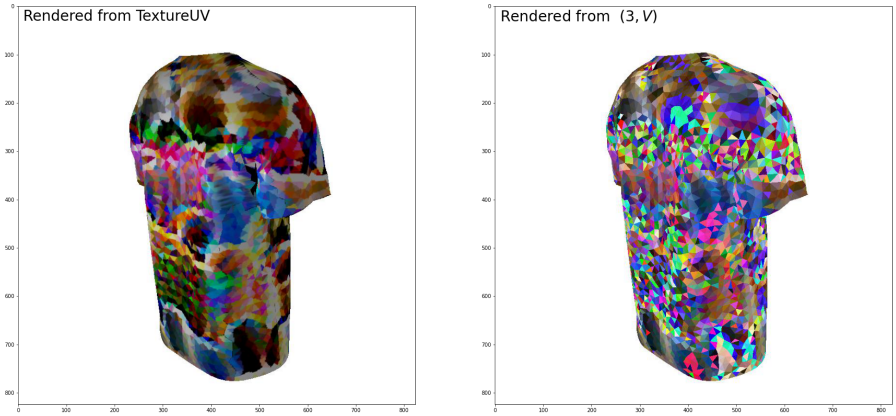
- 9.5 experiment 8： 尝试不均匀地sample角度，因为之前 random angles 均匀采样（as the red line shows）会导致面积较小的衣服侧面对抗性较低
  - evaluate the model once every 5 epoches, divide the 360° angles into 36 intervals and estimate the loss ℓ_i in each interval.
  - Sample $azim \leftarrow D$, where $D(i) = \exp(\alpha \ell_i) / \sum_i \exp(\alpha \ell_i)$
- 9.7 I test the performance of different α. Since the final loss ranges from 0.1 to 0.25, I try $\alpha = 10, 15, 20$ so that the ratio of sampling probability is about ~ 10.
  - $\alpha = 10$ is too weak to be efficient; while $\alpha = 20$ is too aggressive to converge.
  - $\alpha = 15$ is balancing.



- 9.9 I regenerate an obj file for Tshirt using meshlab.
  - Details: Set up 4 cameras (at 0,90,180,270 degree) and auto-generate the maps from mesh to texture.



- 9.10 Map the $(3, V)$ vector to the uv texture.
  - Details: Draw a monochrome triangle on the texture for each face according to $(3, V)$
  - The expressive power of uv texture is much stronger than $(3, V)$. The reverse mapping thus requires more restriction.
  - Render from the texture again using the UV map.

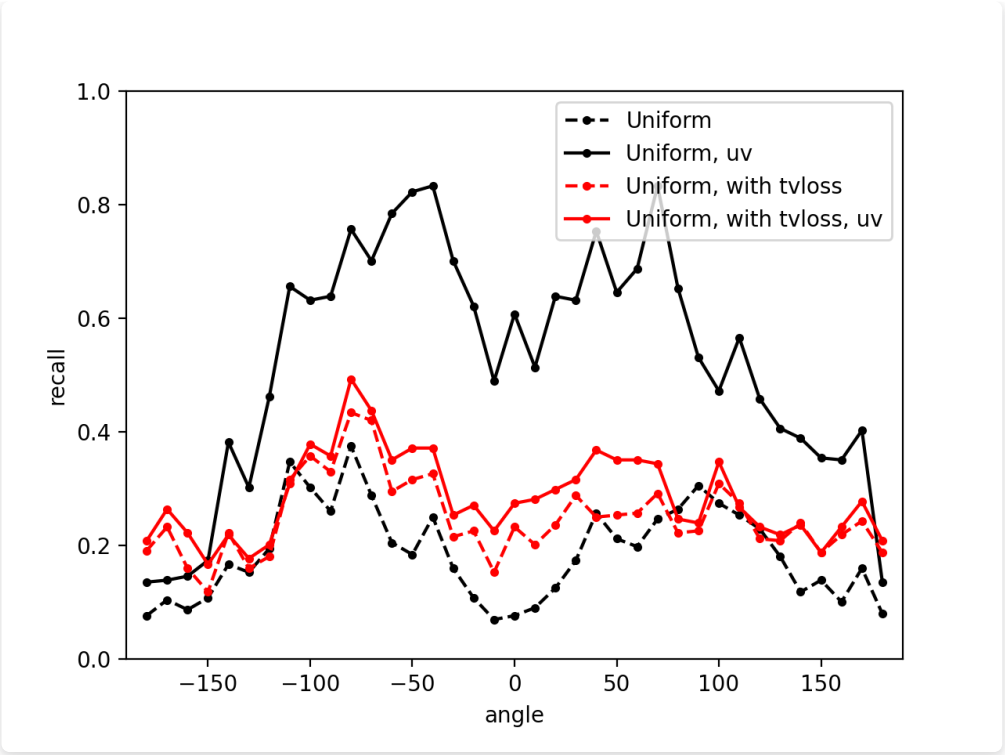


  - ~~The uv-rendered tshirt is smoother in color but much less adversarial than the atlas-rendered one.~~
  - ~~It is necessary to create a precise mapping from UV to Atlas, which would enable the pipeline of training an adversarial uv texture.~~

    - ~~An observation is that the lateral part of the uv-rendered tshirt gives lower recall, which is counterintuitive since the lateral part usually performs worse than other angles with less surface area.~~
    - ~~A possible (yet not necessarily true) explanation: the task of the lateral parts is harder so it is trained more robust to random deviations.~~
    - ~~(9.12) Combining two meshes using uv texture causes conflicts: mesh of man cloaks the mesh of tshirt~~
    - This bug is due to incompatible texture size of two meshes. **Fixed**. (9.16)
- Transfer uv texture back to $(3, V)$ by interpolation (3% deviation from original $(3, V)$ representation).

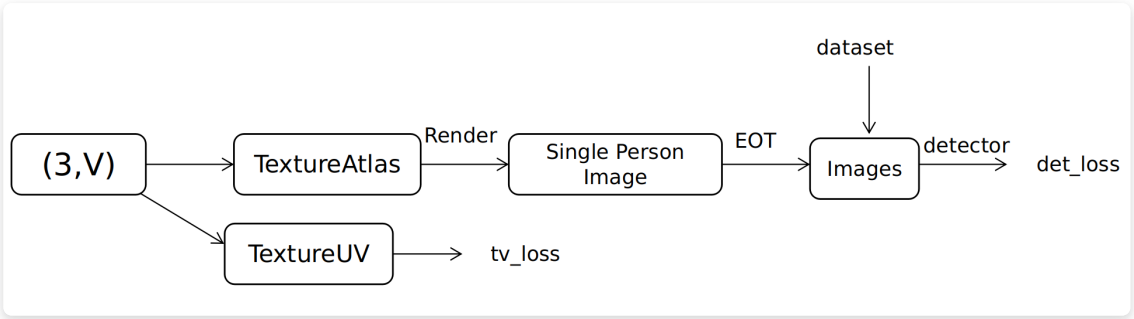
- 9.15 Enables the fast transfer from (3,V) to 2d texture in pipeline and calculate the corresponding TV loss of the 2d texture. `loss = det_loss + a * tv_loss`

    - Details: `uv = vec[:,maps[:,:]]`



Recall comparing tv loss

- Current Pipeline:

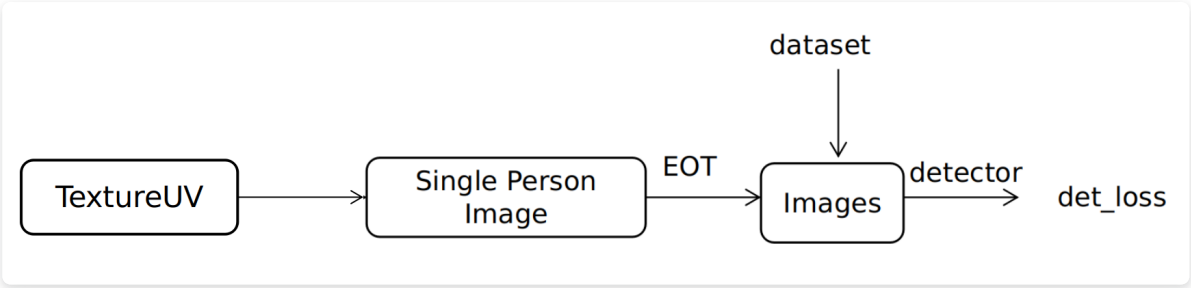


Pipeline

- Next step: to enable the rendering process directly from TextureUV.
  - Replaces TextureAtlas and (3,V) with TextureUV
  - Facilitates direct modification on Tshirt cloth
- 9.16 Merge multiple pieces of texture maps into one.
  - Details: Regenerate an obj. for man with nonoverlapping texture map.
  - Load the origin obj. file using atlas and transform it into (3,V) form.
  - Read the new obj. file by hand and draw each faces using PIL.draw.

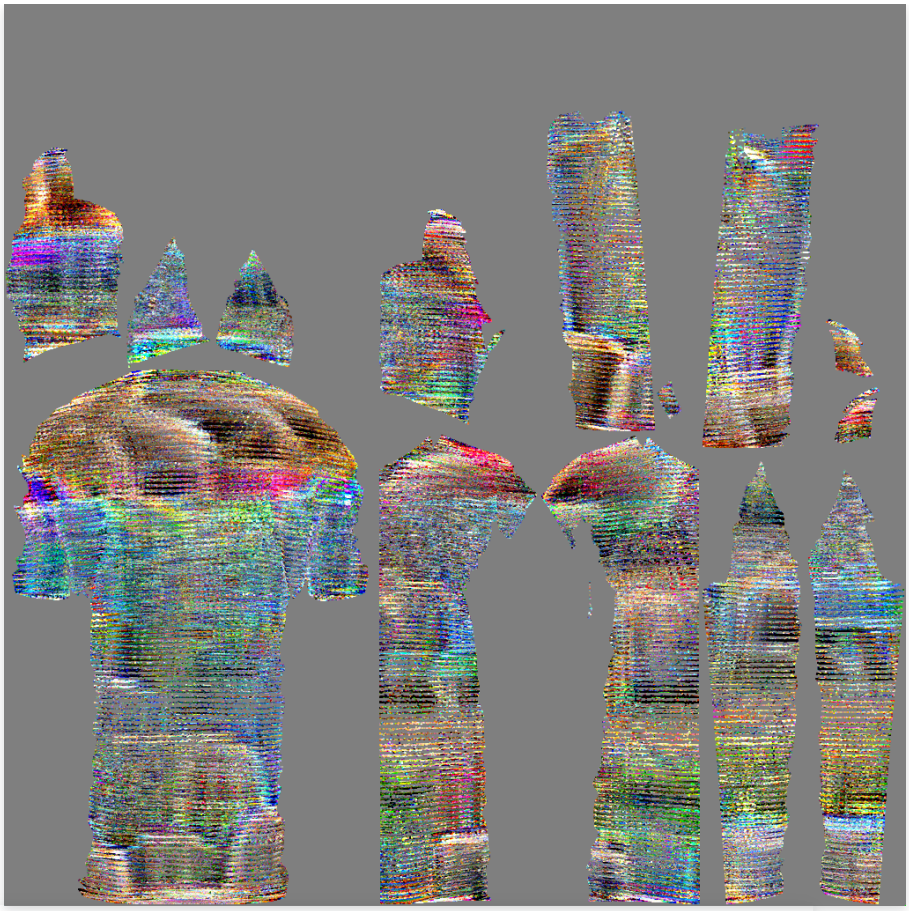
Man texture

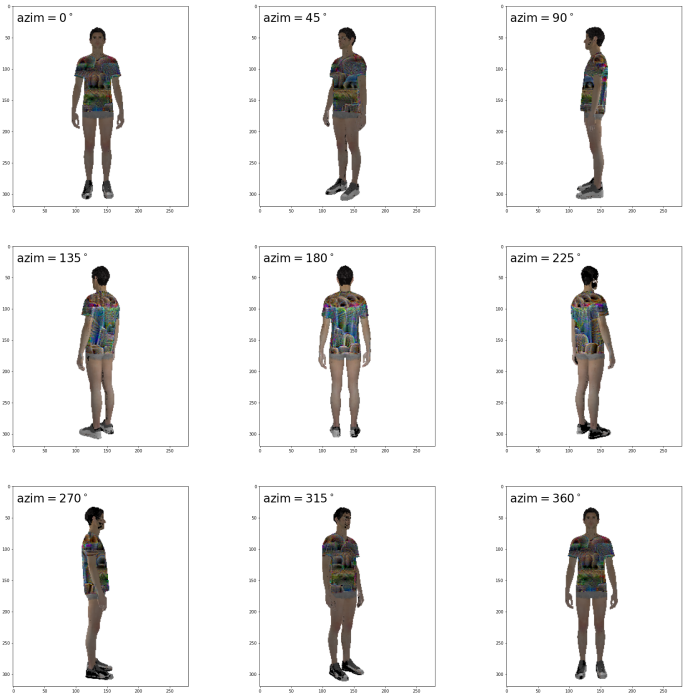
Pipeline:



Pipeline

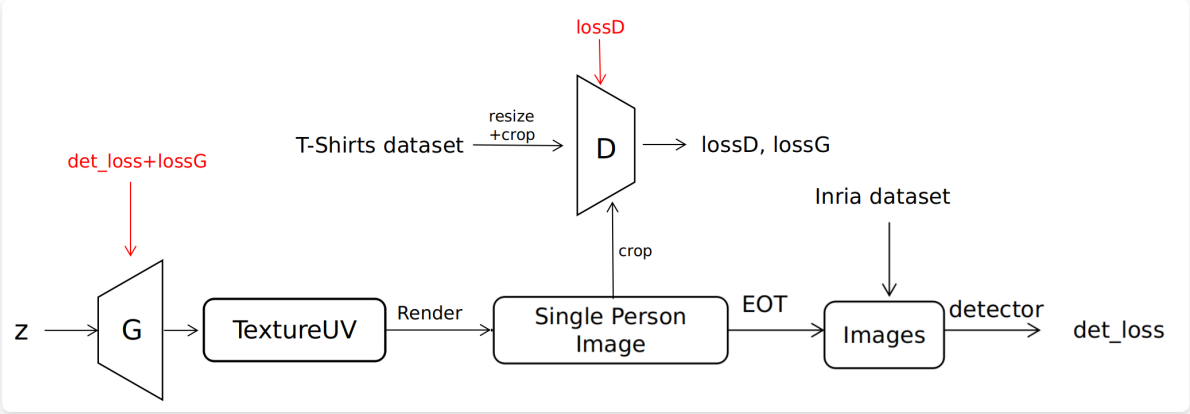
Results:





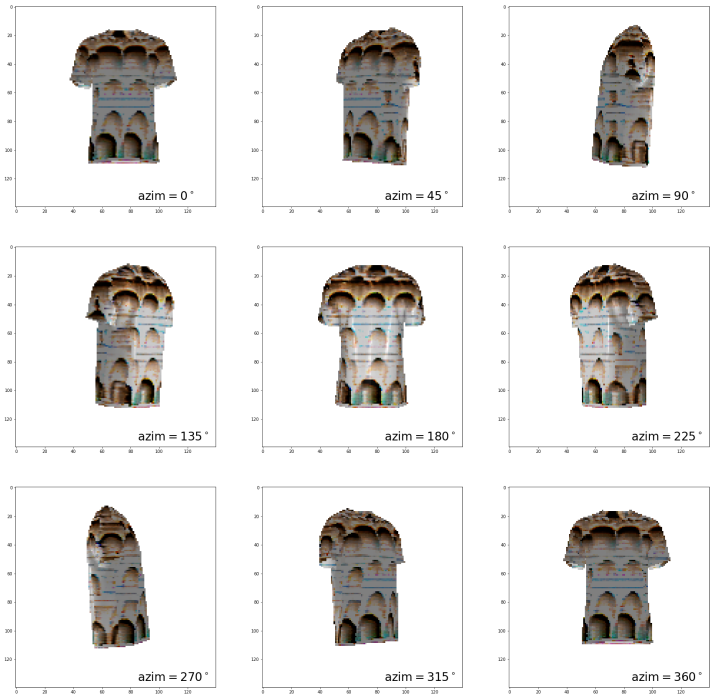
left: Texture

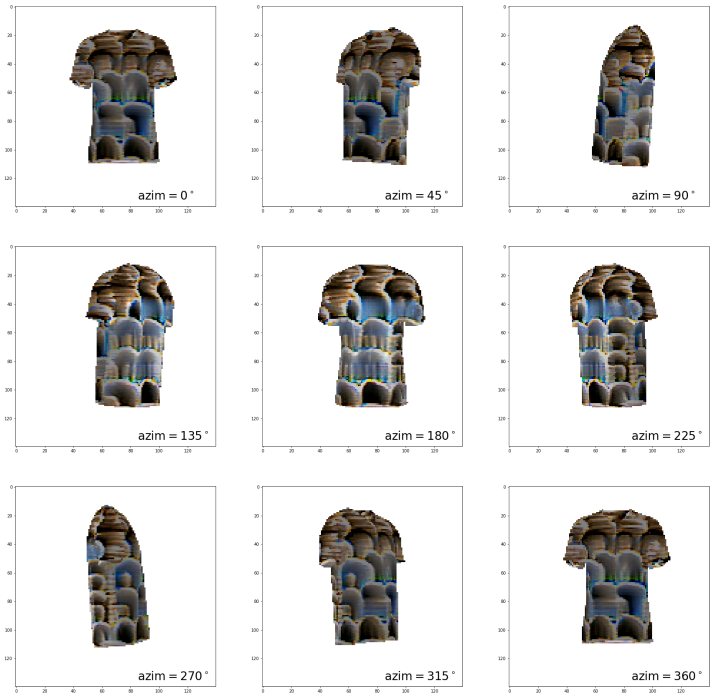
right: Rendered figures



GAN pipeline for generating natural textures

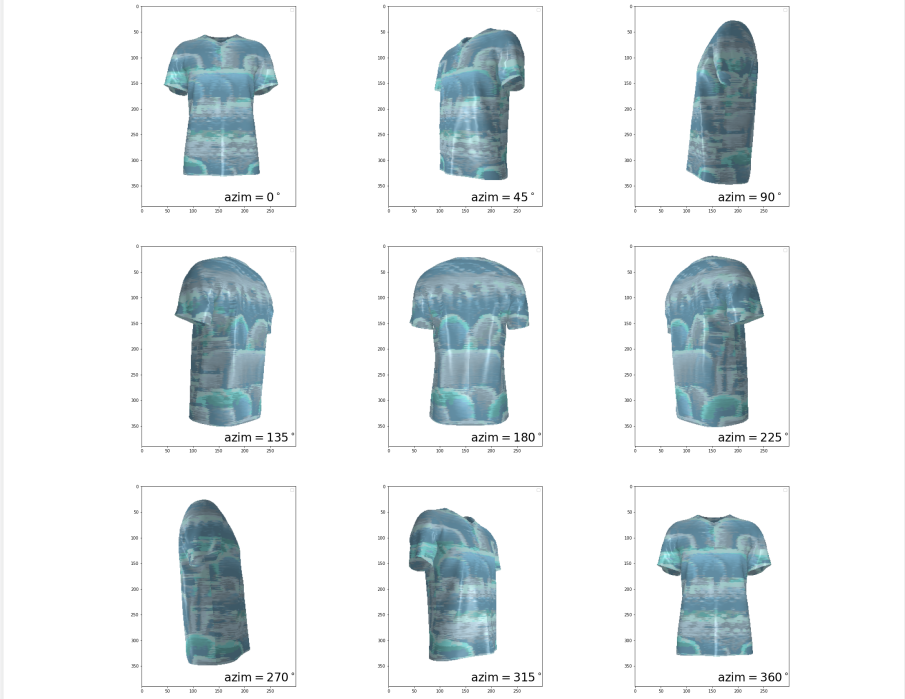
- Collect data of fashionable T-shirts (about 1300 tshirt clean images)
- Use WGAN to generates TextureUV similar to normal T-shirts
- $z \in \mathbb{R}^{128}$, sampled from $\mathcal{N}(0, I)$.
- May require training of z.





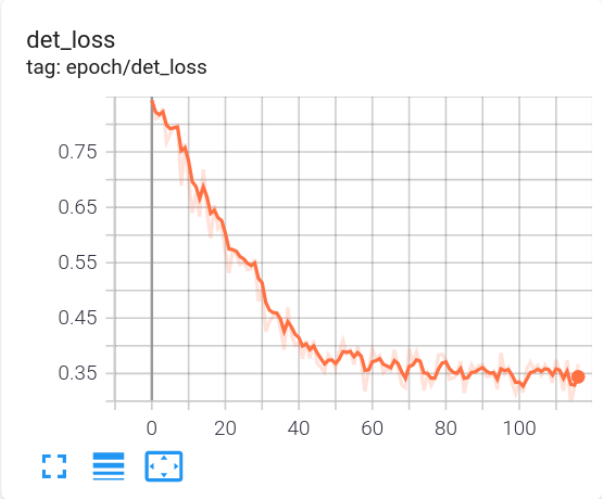
left: WGAN, Loss = det loss + 0.04*LossG; right: Loss = det loss

- Problems: GAN 不稳定, 且 generator 学不到数据中的style
    - 数据集style更集中 ----> 格子衫
    - ~~Reconstruction，then train latent vector for adversarial loss in a lower dimensional manifold~~
    - GAN 问题： 渲染出来的图片和真实拍的看起来不一致，而且必须有各个角度的真实图片



left: Randomly generated, dim = 128. HSV(H[180,200], S[0.2, 0.4], V[0.8,1.0])

right: Randomly generated, dim = 16. HSV(H[180,200], S[0.2, 0.4], V[0.8,1.0])



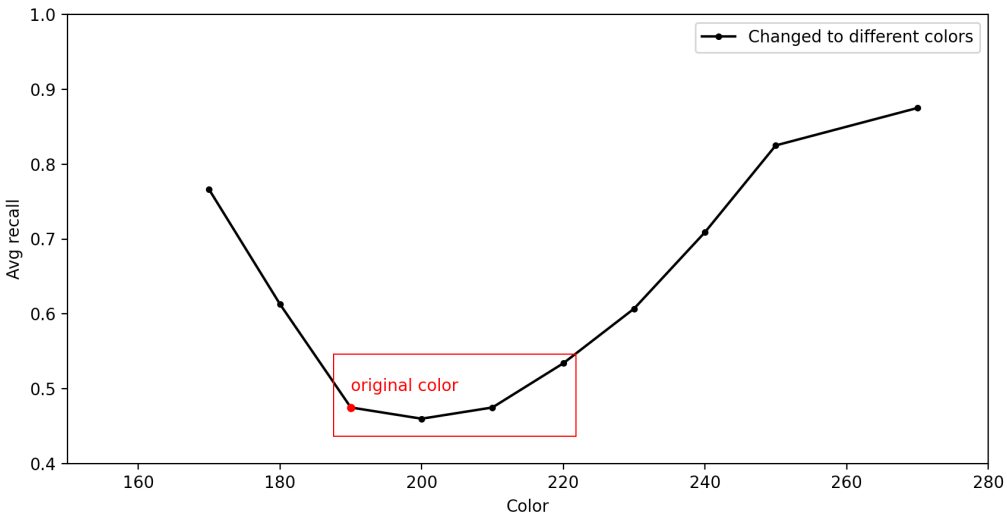
generating blue textures, detection loss

Ideas from Design:

- 多个图层叠加, RGBA表示
- 用 Bezier 曲线参数化图案 (differentiable)

10.19 **An interesting observation**

- I perturb the blue texture with colors in $[180, 200]$ by:
- It turns out that the texture with translation **remains adversarial**.



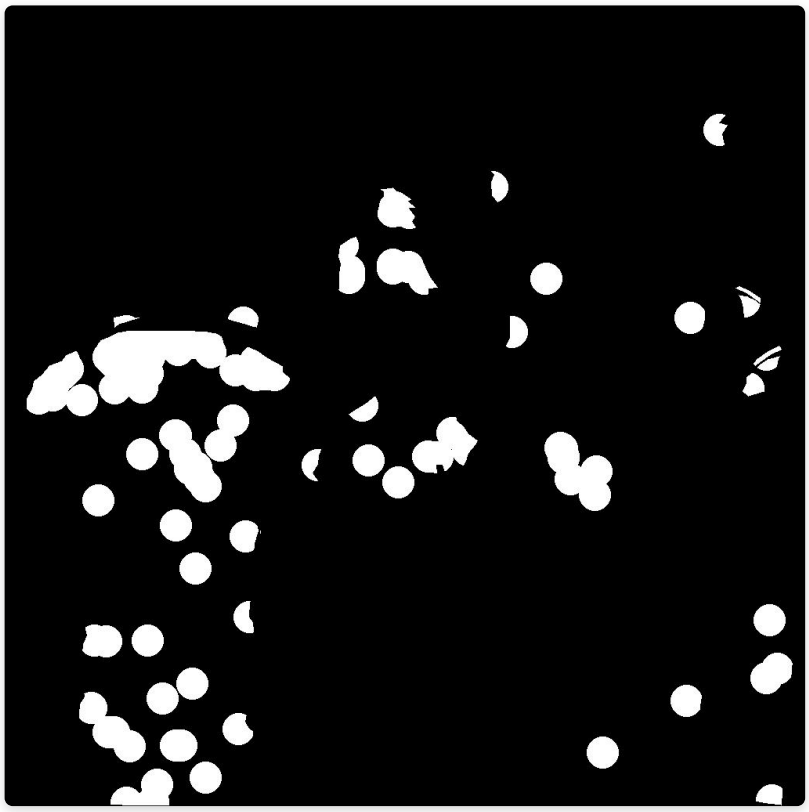
Translatation of color. x-axis stands for the center color.

- Explanation 1: `(h,s,v)` $\rightarrow$ `(r,g,b)`. When $h \in [180, 240]$ and s, v are fixed, `r,b` never change and `g` changes linearly.
- Explanation 2: Adversarial examples for mask-rcnn rely more on silhouette (or the difference of colors) but less on colors.

RGBA blending: Add c_2 on top of c_1

10.20 **I try to add another layer of red on a already trained blue layer**. （一层层叠加）

- the `mask` is derived from descending order of $\langle \nabla \ell(c_1), (c_2 - c_1) \rangle$.



Descending order of gradient, with circles, AND

- **Cannot converge.**

mask 要求：色块比较连续、（最好）可优化

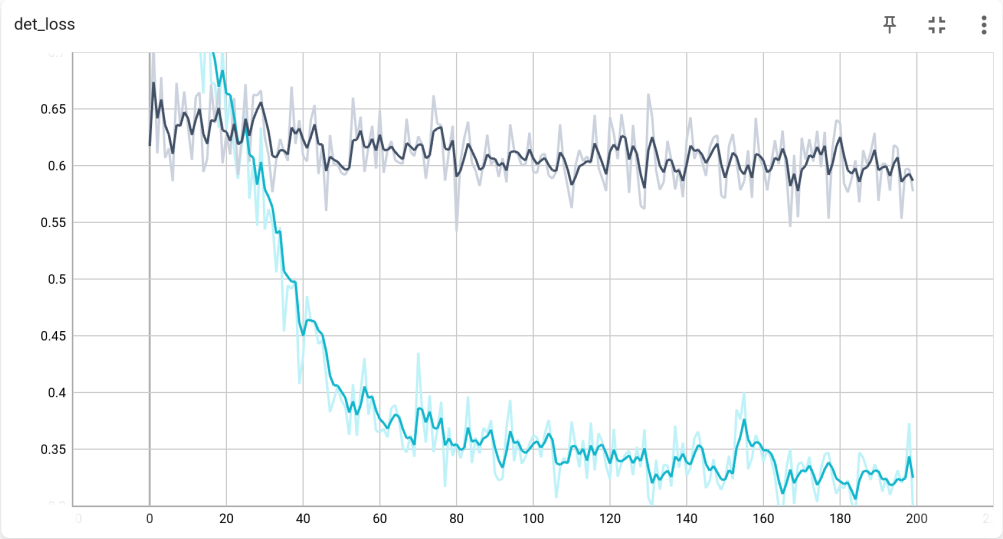
10.23 **Train two layers at the same time?**

- Generate 0/1 mask randomly using PIL.ImageDraw

200 random geometries, XOR

- Output `3*num_layers` channels in the last deconvolution layer.
- Apply `texture = texture*(1-mask) + new_texture*mask`

2 layers, Blue([200,220]) + Red([0,20])

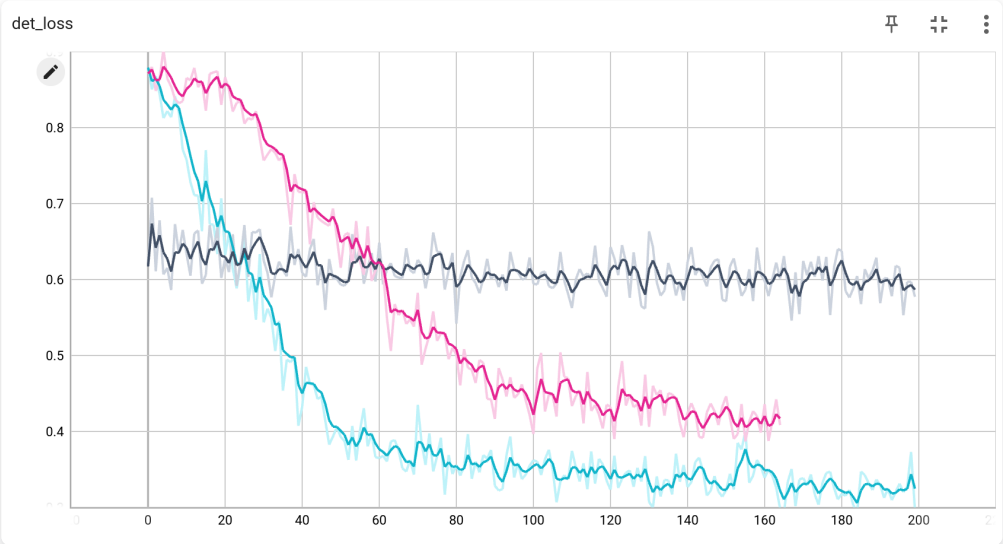


Gray: add a new layer on a trained layer

Blue: train two layers at the same time

10.24 **Trained with random mask**

- Change the mask randomly **during** the trainig process.



Gray: add a new layer on a trained layer

Blue: train two layers at the same time

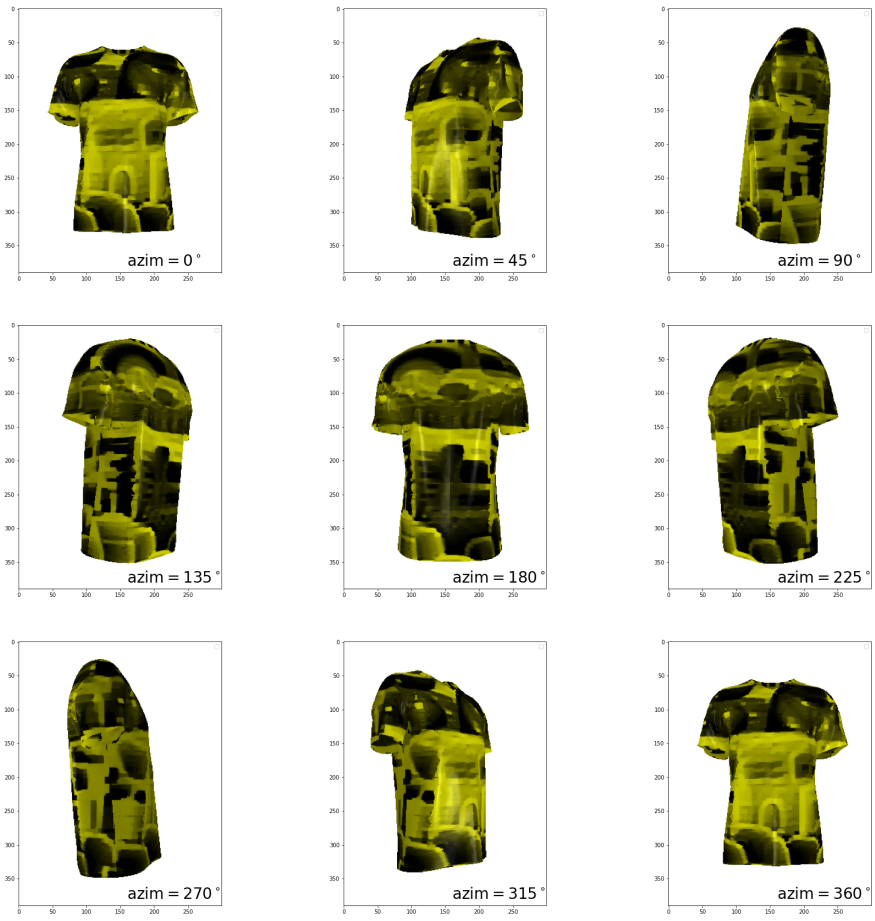
Red: train two layers with random mask

11.7 **Goal**: To design textures that are **smooth/continuous/monochrome in several different patches**

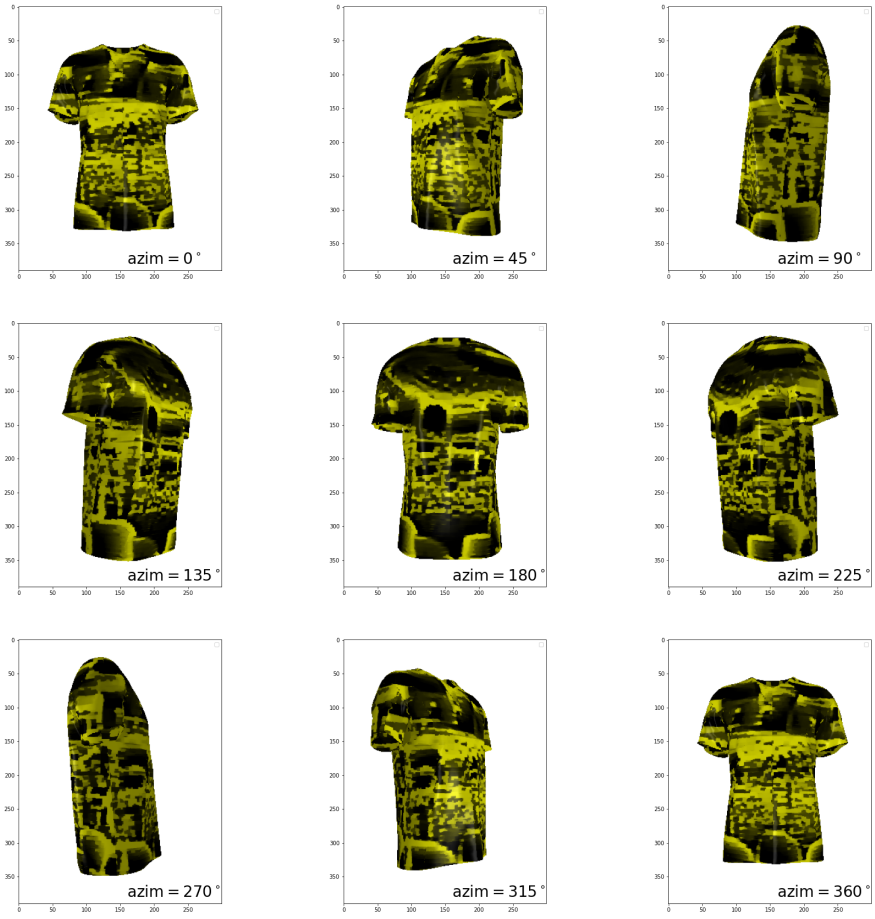
- Previous idea: train a 0/1 mask and join two monochrome patches together
- Problem: 0/1 mask is hard to optimize

- Define purity loss to soften this constraint:
  - For mask $m \in [0,1]^{w \times h}$,
- Moreover, to push the mask to approximate 0/1, learn logits of mask x, so $m = Sigmoid(x)$.
- (This also cancels the optimizing restriction of $m \in [0,1]$.)

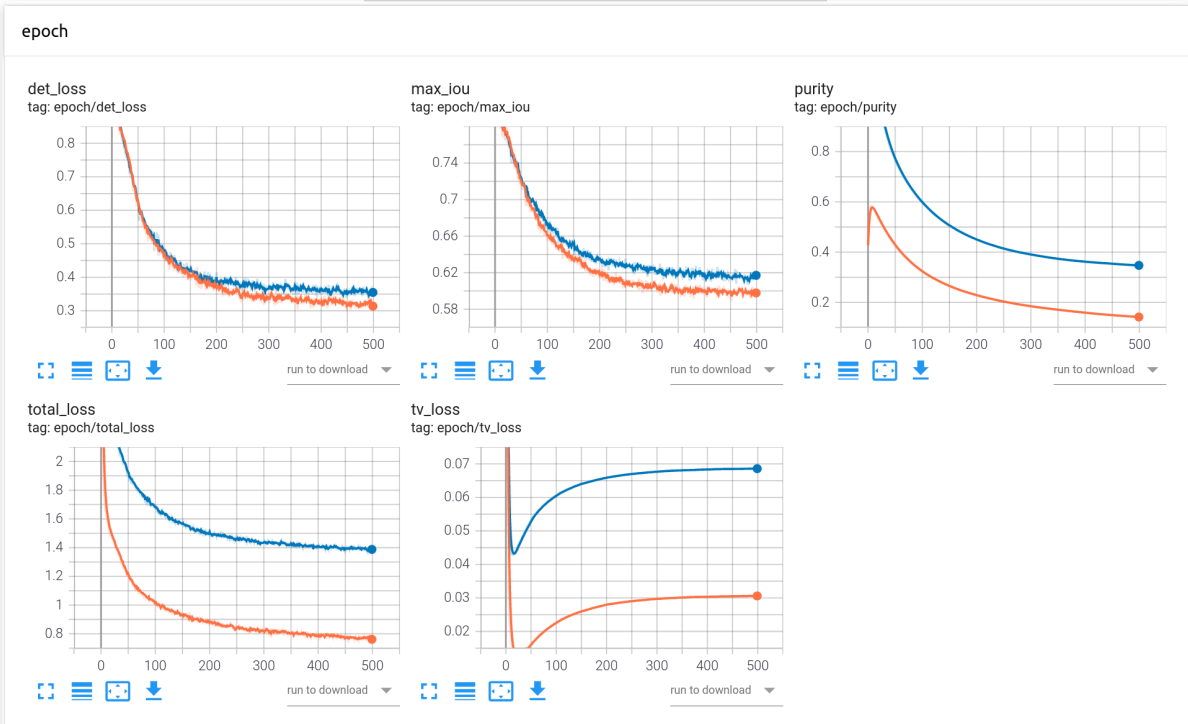
- Experiments:
  - Texture: $tex = m * yellow + (1-m) * black$.
  - Note: this forms quite a narrow space for optimization, since each pixel is now restricted to a line.



Yellow + Black, optimizing mask, β=1



Yellow + Black, optimizing mask, β = 2



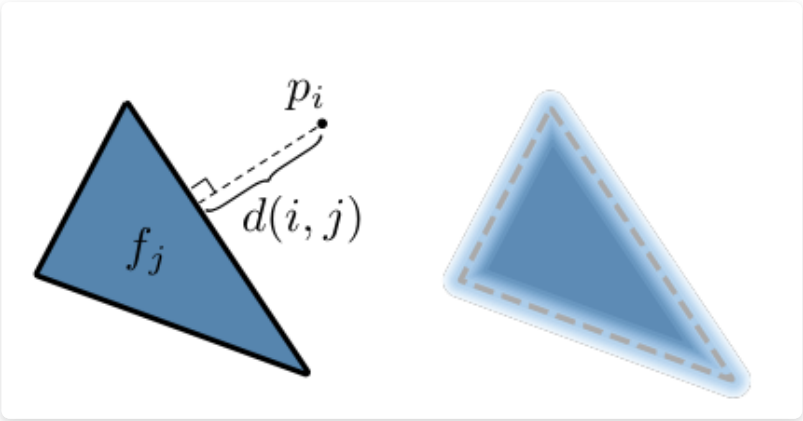
Orange: β=1

Blue: β=2

Tests	Average Recall
RGB, UV	0.191
Randomly Generated, dim=128. Green (H[100,120], S[0.5,0.8], V[0.3,0.6])	0.465
Randomly Generated, dim=128. Blue (H[180,200], S[0.2, 0.4], V[0.8,1.0])	0.475
Two layers, blue[200,220] + red[0,20], fixed mask	0.479
[0,1] Mask yellow + black, $\beta = 1$	**0.458**
[0,1] Mask yellow + black, $\beta = 2$	**0.534**

11.22 How to optimize geometric shapes?

- 可微渲染：Probability map
- **Triangles** (a, b, c) (paper)
  - 希望 probability map 是关于三角形顶点的可微函数。
  - $\mathcal{P}_{ij} = \text{Sigmoid}(\alpha \delta_{ij} d_{ij}^{\beta})$
  - where $\delta_{ij} = +1$ if (i, j) inside the triangle and $\delta_{ij} = -1$ if outside.
  - d_{ij} : the shortest distance from (i, j) to the triangle.
  - so $\delta_{ij} d_{ij}$ is actually the ***signed distance function*** of the triangle.



Triangle

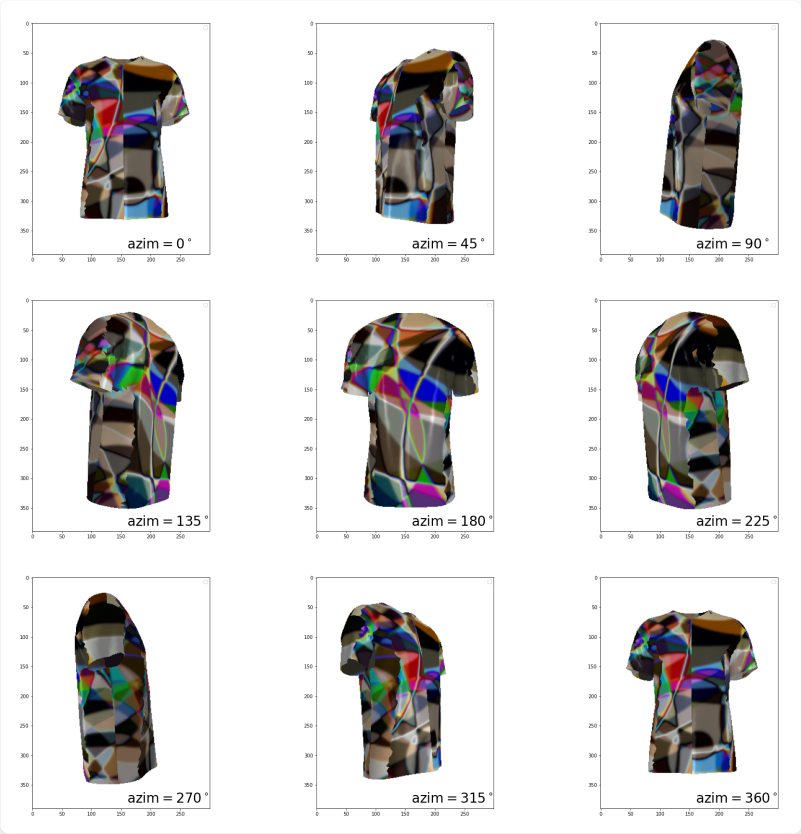
Image from: here

- **Circles** (p_0, r_0)
  - $\mathcal{P}_{ij} = \text{Sigmoid}(\alpha(r_0 - r)^{\beta})$, where $r = \|(i, j) - p_0\|_2$.

- **XOR**
  - N triangles and M circles with probability maps $\mathcal{P}_k$.
  - $\text{mask} = f\big((\sum_k \mathcal{P}_k)\%2\big)$.
  - where $f(x) = x$ if $x \in [0, 1)$ and $f(x) = 2 - x$ if $x \in [1, 2)$
- Next step:

- Other geometries (Ellipse, arbitrary curve)
- Dynamic number of geometries

Tests	Average Recall
60 circles	0.661
100 circles	**0.591**
60 circles + 20 triangles	0.648
100 circles, $\alpha_{circle} = 0.5$.	0.567
100 circles, dynamic blur α_{circle}	0.512



100 circles

100 circles

11.22 ~ 12.6

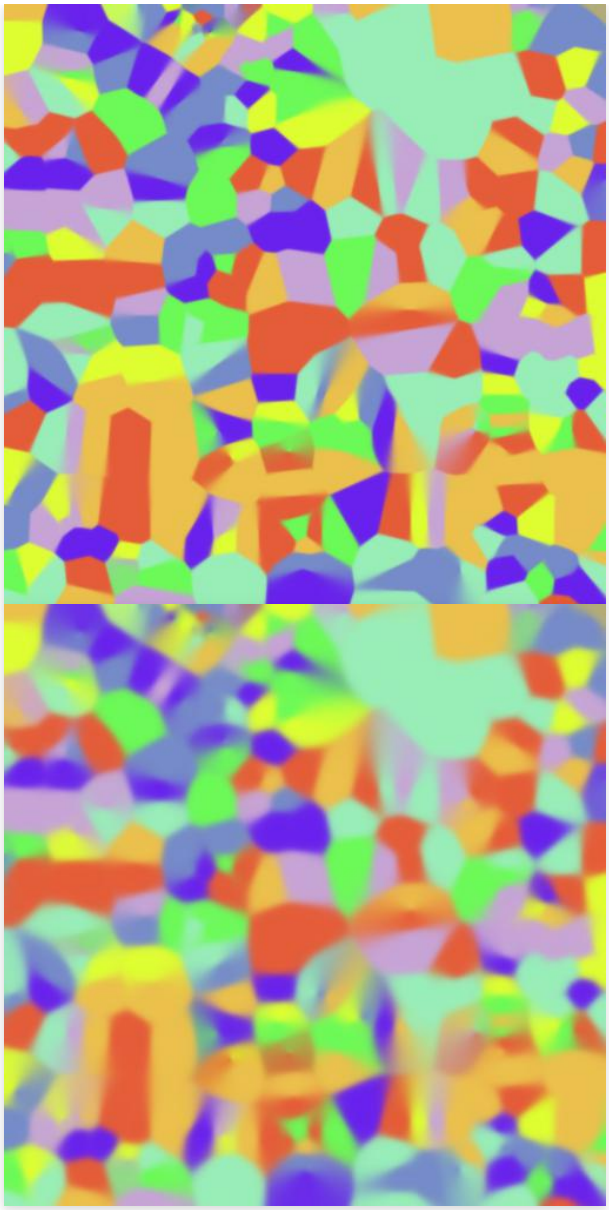
1. Criterion change

- Confidence threshold: from 0 to 0.6

Tests (conf_thres = 0.6)	Average Recall (%)
100 circles, dynamic blur α_{circle}	51.2 --> 9.66
8 colors * 30 points, $\alpha = 5$	18.8
8 colors * 50 points, $\alpha = 5$	11.0
8 colors * 50 points, $\alpha = 5$, $\alpha' = 3$	9.64
8 colors * 50 points, $\alpha = 5$, $\alpha' = 1$	20.68
5 colors * 80 points, camouflage. $\alpha = 2$.	11.91

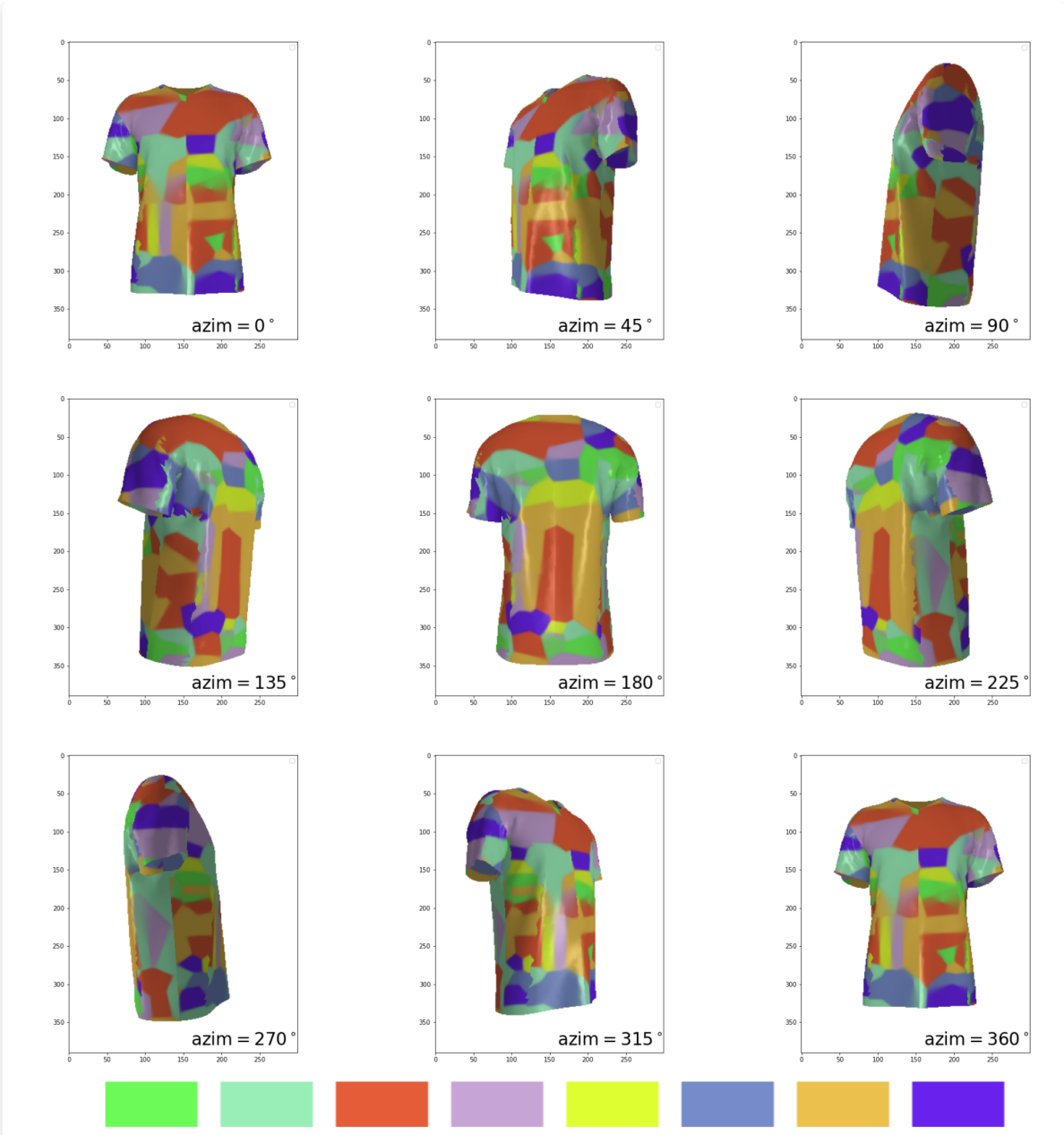
2. Restrict number of colors

- XOR is good for 0/1 mask, but **not flexible** for controlling colors
- Approximate **Voronoi graph**
- Parameters:
  - C different colors, N control points for each color.
  - Control points: $B = (b_{ij}) \in \mathbb{R}^{2\times C\times N}$. **Fixed** colors $C = (c_i) \in [0,1]^{3\times C}$
  - 仅优化控制点 B，优化形状
- For pixel x:
  - $p_i^{(x)}$ is the weight of color i at pixel x.
  - α is the hyperparameter that controls the blur radius.



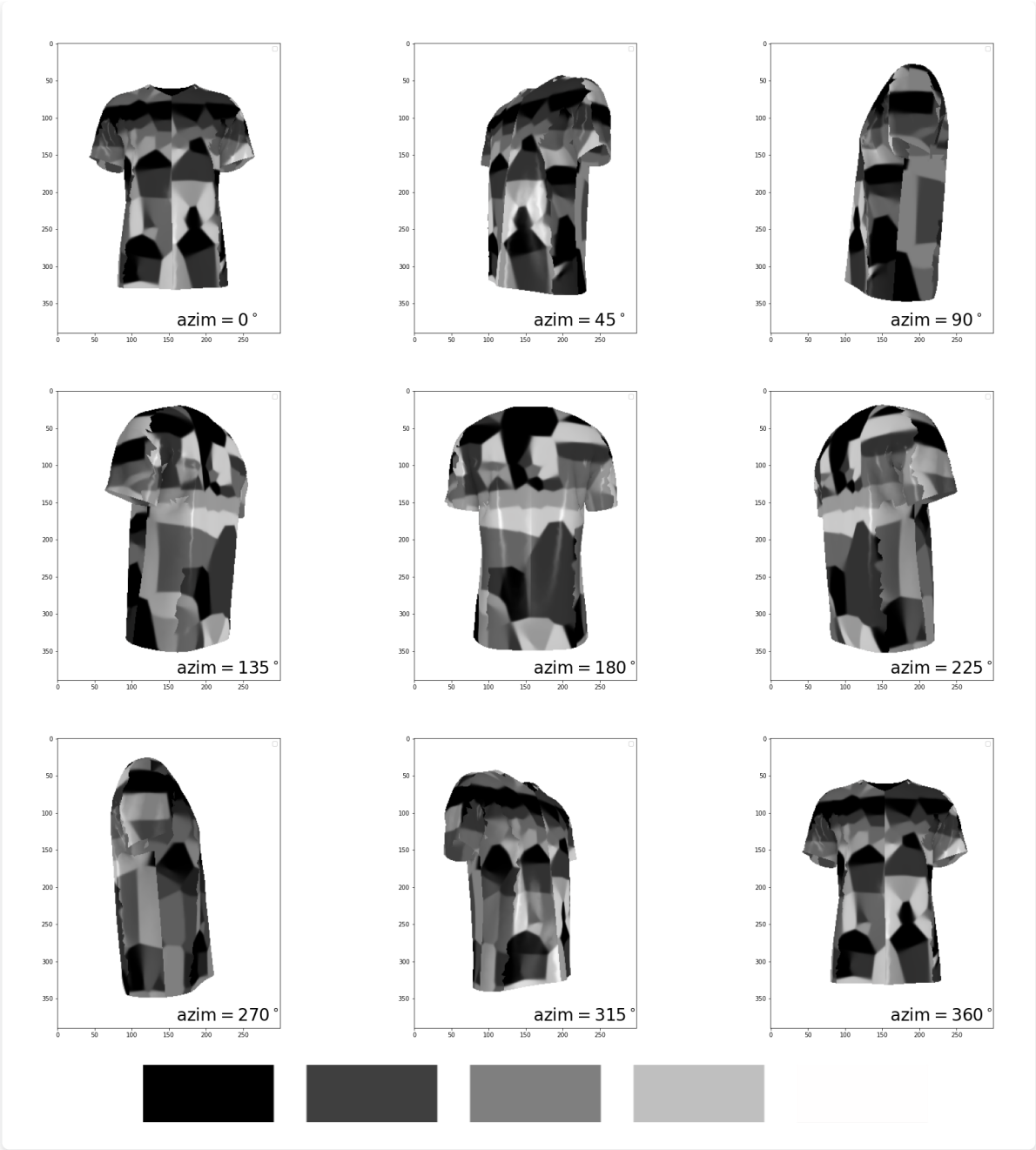
left: alpha = 1 right: alpha = 3

maximize likelihood + adv loss



8 colors x 50 points

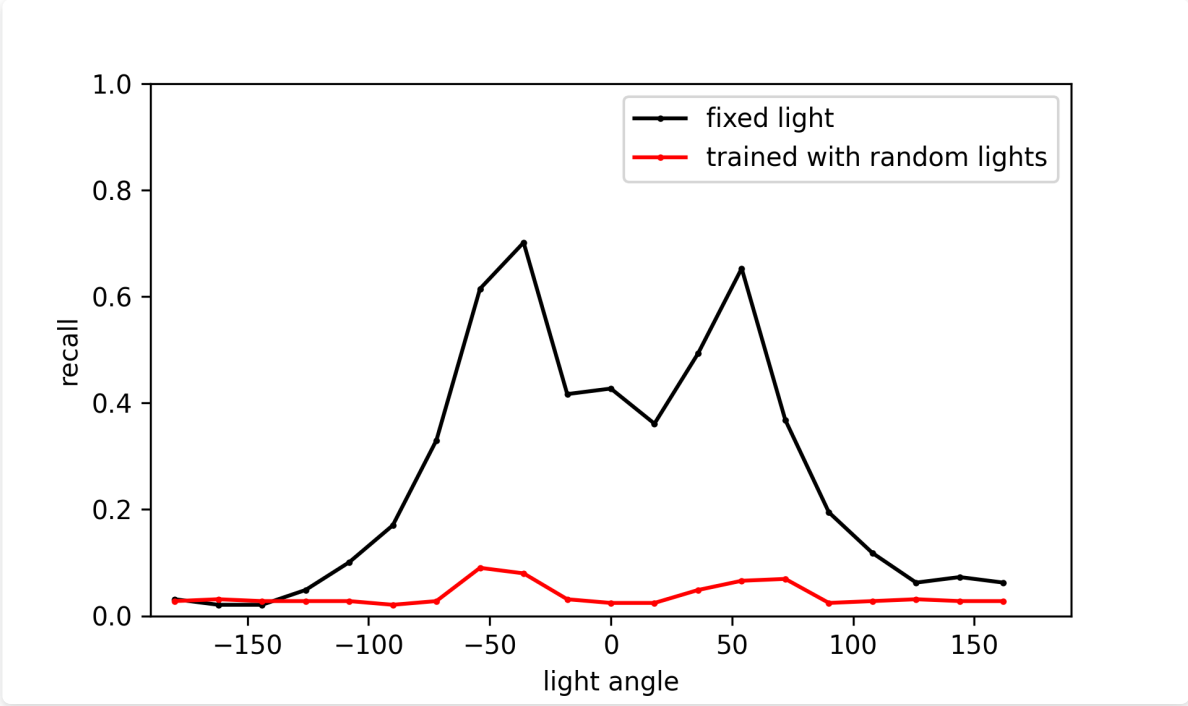
5 colors, camouflage, 80 points



5 colors, grey, 80 points

3. Random Lights

- Changes on light condition may hurt adversarial properties.



8 colors x 50 points, camouflage colors

4. Mesh perturbation (Not implemented yet)

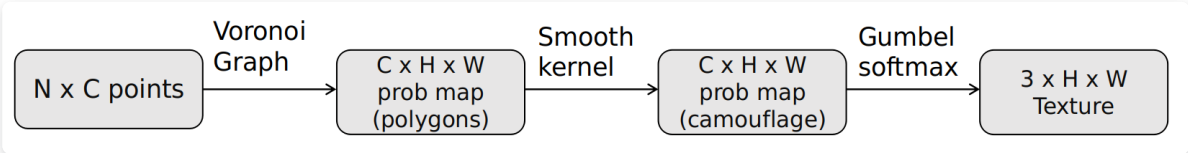
- Randomly add perturbations to vertices of T-shirts mesh.
- T-shirt Mesh:
  - Vertices `(3,N)`. $p(i) = (x_i, y_i, z_i)^T$.
  - $p'(i) = p(i) + f(p(i), r)$.
- Perturbation $f(p(i), r)$ must be continuous over x_i, y_i, z_i. r stands for randomness.
- Candidate functions:
  - $f(p, r) = \left(A_1\sin (\vec k_1 \cdot \vec p + r_1), A_2\sin (\vec k_2\cdot \vec p +r_2), A_3\sin (\vec k_3 \cdot \vec p + r_3)\right)$
  - $f(p,r) = A\vec n \sin(\vec k \cdot\vec p + r)$. (Perturb along normal direction $\vec n$)

Generate camouflage texture:

Normal camouflage texture generator:

- 对于任意一个像素点，计算邻域 $k\times k$ 范围内每种颜色的数量

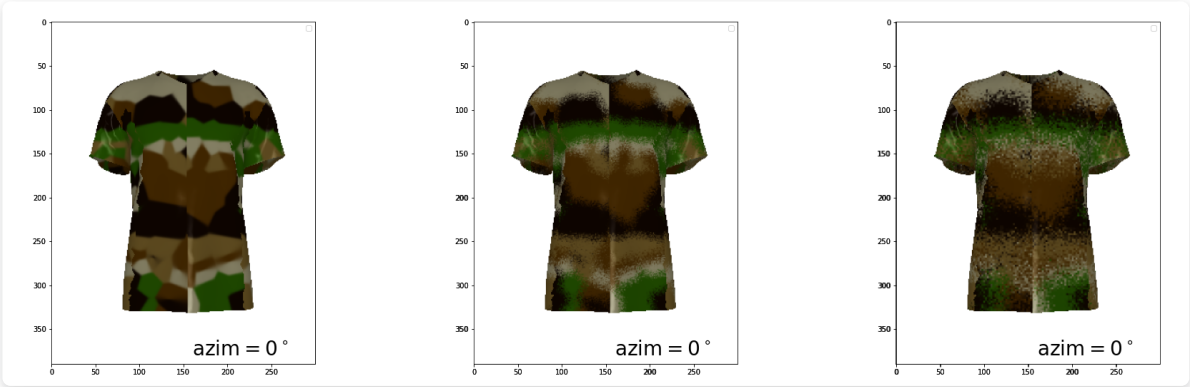
- 因为我们生成的 polygons 本身已经是用 probability map 表示的，只需要用一个 $k\times k$ 卷积核进行柔化即可。
- Use Gumbel-softmax to sample colors for each pixel.



pipeline of generating a camouflage texture

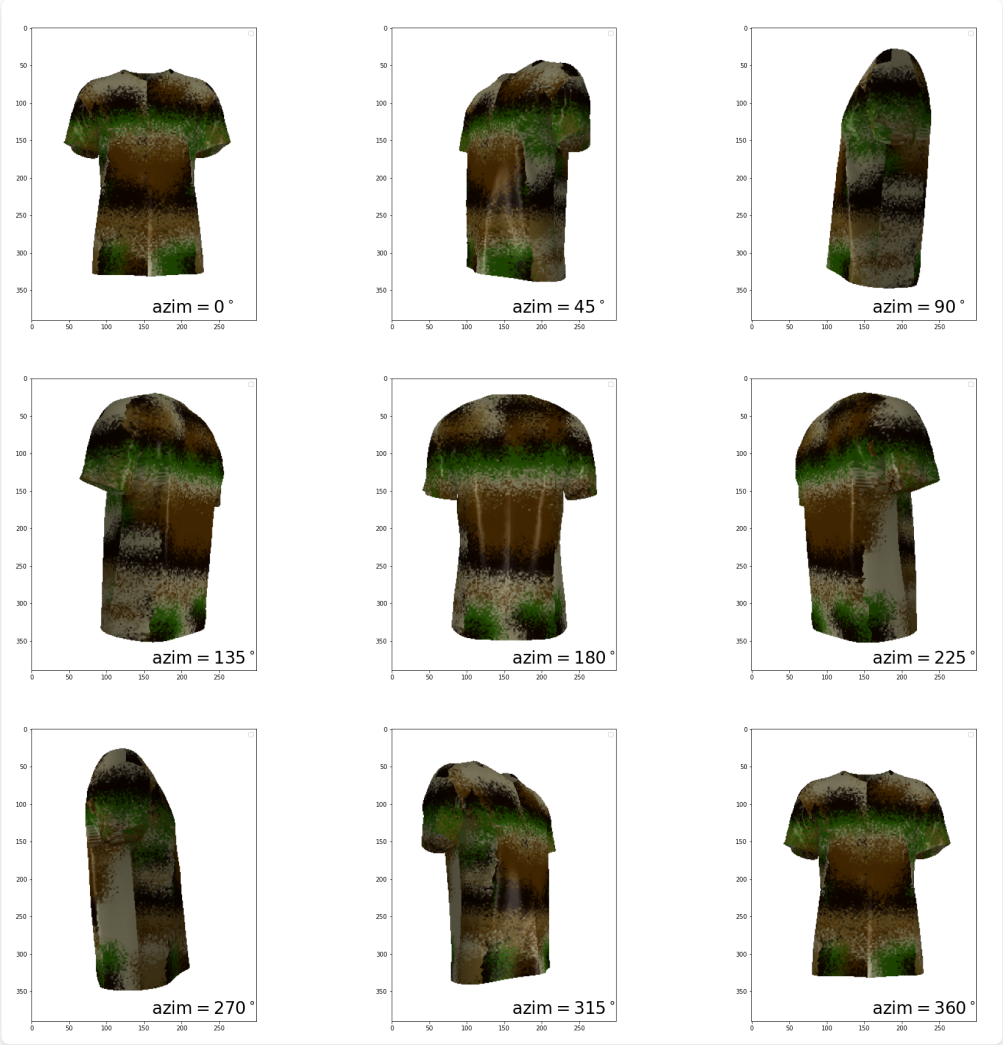
Details:

1. Specify a fixed seed of Gumbel random variables. (Train one texture instead of a distribution of texture)
2. Lower resolution: 在 512 x 512 pixel space 上随机点太小， 如下图（中）。降低分辨率到 $1/d$ 倍.

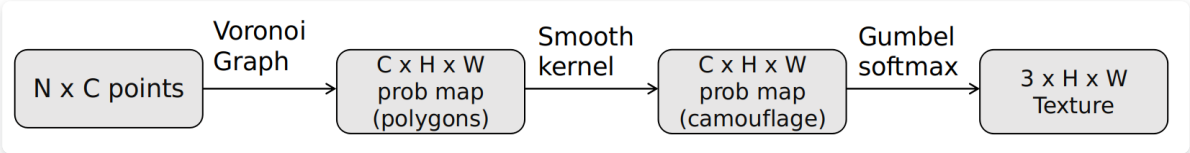


left: polygon; middle: k = 9; right: k = 9, d = 2

Tests (conf_thres = 0.6)	Average Recall (%)
Polygon (Camouflage colors)	11.91
Directly transfer from polygon	70.8
Gumbel-softmax trained	53.23
Gumbel-softmax with fixed seed	31.42
Gumbel-softmax with fixed seed, d = 2	**18.78**
log likelihood	20.67
Mesh perturbation scale = 0.05	28.39



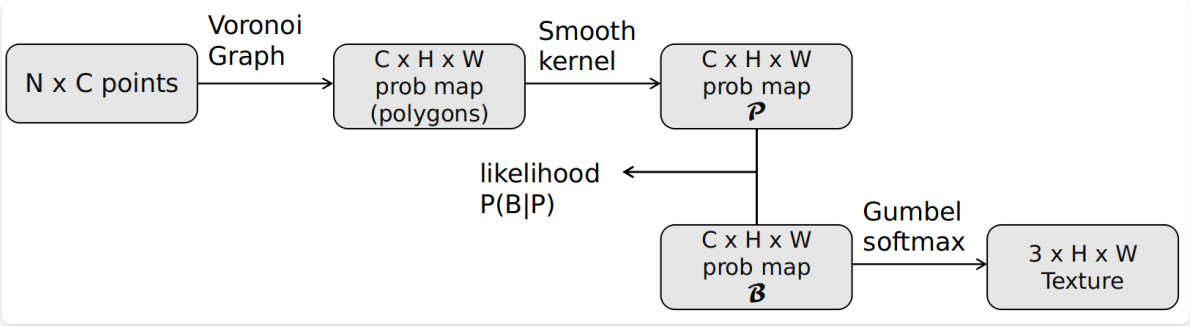
k = 9, d = 2



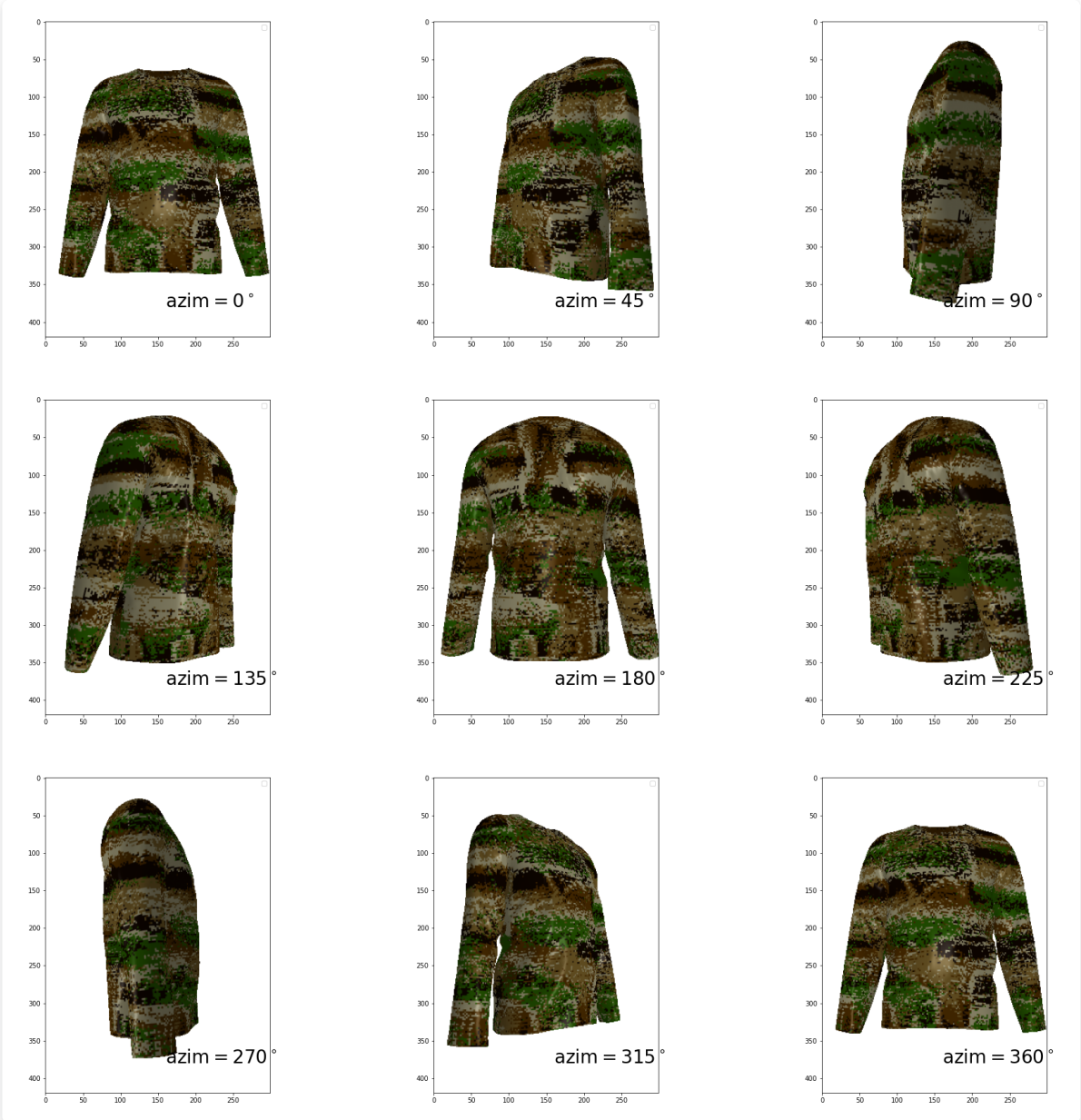
a pipeline of generating camouflage textures

Another method:

- 保持pipeline前半部分，生成一个具有迷彩风格的 probability map P
- 同时优化一个具有迷彩色彩的 probability map B，对 B 使用 Gumbel softmax 再生成 3 x H x W 的材质
- minimize: detection loss + $\Pr (B | P)$.
- allow 2d textures to slightly deviate from permitted style P

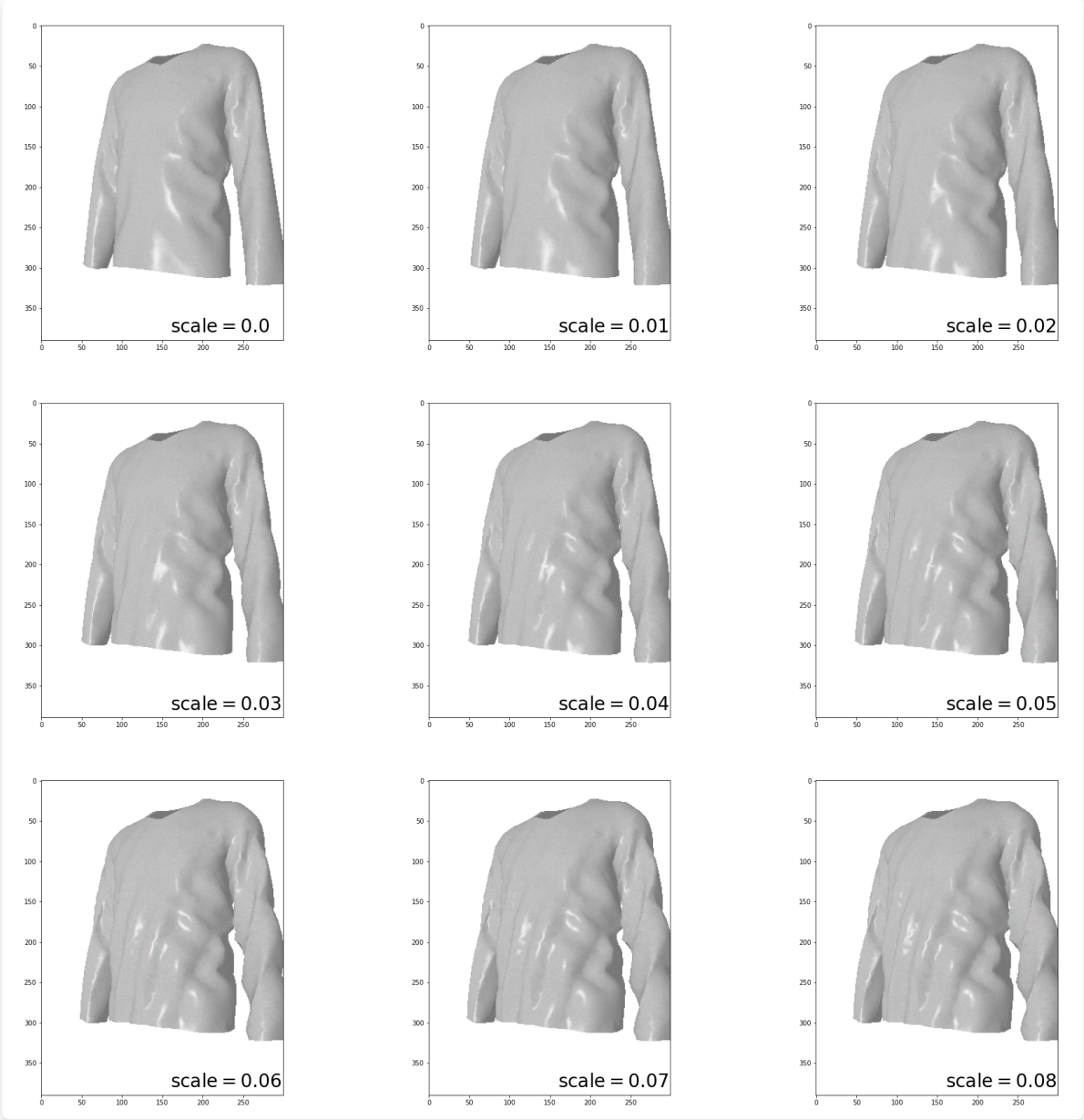


another pipeline of generating camouflage textures



Random mesh deformation

- For a given mesh M with vertices x_i, generate offset
  - This offset is smooth and continous
- $M^\prime = M + \delta$.



Mesh perturbation

Code: Adversarial Texture

1 training_texture.py (Main)

- adversarial cloth: `[1(batch),3(RGB),width, height]`
- Random Crop Attack (RCA), Toroidal Crop Attack (TCA) differs only at `random_crop`

2 tps_grid_gen.py (TPS)

- Initialize: Using a $N\times 2$ array, denoting the N target control points. Then construct the TPS kernel matrix as shown above. `target_control_points`: $\hat p_i^{(x)}, i =[1,\dots, 25]$.
- `source_control_point` is sampled with small disturb from `target_control_points`, which stands for $\hat p_i^{(z)}$.
- `source_coordinate = self.forward(source_control_points)`.
  - forward function calculates
  - Then calculate `source_coordinate` by equation $\ref{delta}$.

```
mapping_matrix = torch.matmul(Variable(self.inverse_kernel), Y)
source_coordinate = torch.matmul(Variable(self.target_coordinate_repr), mapping_matrix)
```

- Finally, use `F.grid_sample` to map the adversarial patch to `source_coordinate`.

3 load_data.py

3.1 MaxProbExtractor

- Extracts max class probability from YOLO output.
- YOLOv2 output: [`batch`, (`num_class` + 5)×`num_anchors` , $H \times W$]
- `num_class` + 5 = 85.
  - 0~3: x,y,w,h
  - 4: confidence of this anchor (objectness)
  - 5~84: class probability $\Pr[class_i|obj]$ of this anchor
  - for `func = lambda obj,cls:obj`, we only minimize the maximum objectness confidence.

4 random_crop

Crop type:

- None: used for RCA, TCA crop

5 Patch transformer

- randomly adjusting brightness and contrast, adding random amount of noise, and rotating randomly
- `adv_batch = adv_batch * contrast + brightness + noise`
- The training label: (N, num_objects, 5).
- Output: (N, num_objects, 3, fig_h, fig_w)

Paper List

Most parts of this paper list is borrowed from Nicholas Carlini's Reading List.

Preliminary Papers

Evasion Attacks against Machine Learning at Test Time
Intriguing properties of neural networks
Explaining and Harnessing Adversarial Examples

Attacks [requires Preliminary Papers]

The Limitations of Deep Learning in Adversarial Settings
DeepFool: a simple and accurate method to fool deep neural networks
Towards Evaluating the Robustness of Neural Networks

Transferability [requires Preliminary Papers]

Transferability in Machine Learning: from Phenomena to Black-Box Attacks using Adversarial Samples
Delving into Transferable Adversarial Examples and Black-box Attacks
Universal adversarial perturbations

Detecting Adversarial Examples [requires Attacks, Transferability]

On Detecting Adversarial Perturbations
Detecting Adversarial Samples from Artifacts
Adversarial Examples Are Not Easily Detected: Bypassing Ten Detection Methods

Restricted Threat Model Attacks [requires Attacks]

ZOO: Zeroth Order Optimization based Black-box Attacks to Deep Neural Networks without Training Substitute Models
Decision-Based Adversarial Attacks: Reliable Attacks Against Black-Box Machine Learning Models
Prior Convictions: Black-Box Adversarial Attacks with Bandits and Priors

Verification [requires Introduction]

Reluplex: An Efficient SMT Solver for Verifying Deep Neural Networks
On the Effectiveness of Interval Bound Propagation for Training Verifiably Robust Models

Defenses (2) [requires Detecting]

Towards Deep Learning Models Resistant to Adversarial Attacks
Certified Robustness to Adversarial Examples with Differential Privacy

Attacks (2) [requires Defenses (2)]

Obfuscated Gradients Give a False Sense of Security: Circumventing Defenses to Adversarial Examples
Adversarial Risk and the Dangers of Evaluating Against Weak Attacks

Defenses (3) [requires Attacks (2)]

Towards the first adversarially robust neural network model on MNIST
On Evaluating Adversarial Robustness

Other Domains [requires Attacks]

Adversarial Attacks on Neural Network Policies
Audio Adversarial Examples: Targeted Attacks on Speech-to-Text
Seq2Sick: Evaluating the Robustness of Sequence-to-Sequence Models with Adversarial Examples
Adversarial examples for generative models

Detection

Rich feature hierarchies for accurate object detection and semantic segmentation
You Only Look Once: Unified, Real-Time Object Detection
YOLO9000: Better, Faster, Stronger

Physical-World Attacks

Adversarial examples in the physical world
Synthesizing Robust Adversarial Examples
Robust Physical-World Attacks on Deep Learning Models
Adversarial T-shirt! Evading Person Detectors in A Physical World
Universal Physical Camouflage Attacks on Object Detectors
Fooling Automated Surveillance Cameras Adversarial Patches to Attack Person Detection
Can 3D Adversarial Logos Cloak Humans?
Adversarial Texture for Fooling Person Detectors in Physical World

Ideas

- Difference from 3D logo? (What's our goal?)
- Restricted deformation or recoloring from any input cloth?
- Differential deformation of logo (by B-spline?)
- monochromatic, analogous, or complementary colors

我们现在是优先attackiou最大的框，然后小于一定iou threshold的就不训练了，防止过度训练到一些trivial的boxes

牺牲了一些iou比较小但是prob比较大的框，能不能把周围有人的情况下，把周围的人也隐藏起来

object confidence=iou和prob 效果不好

B个角度的取梯度的平均值，weighted mean去加速优先attack

2D的pipeline 饱和度 hsv

色相饱和度亮度

参数化 gan