Abstract
We take a machine learning based approach to adaptive sampling for Monte Carlo Ray Tracing, by using geometric and lighting data obtained through prior renders of scenes.

Motivation
- Monte Carlo ray tracing is realistic, handles complex natural phenomena well.
- Cons: High quality images are expensive to render.

Adaptive Sampling
- Ideally, the number of rays for a given pixel would depend on the sampled pixel’s rate of convergence to the perfect pixel.
- The challenge is thus to predict when a pixel is "close" to the perfect pixel.
- Hypothesis: Pixel value is within convergence threshold.

Our Approach
- Layers of Support Vector Machines to determine whether we would need to increase the number of samples.
- Implementation as pbrt extension (Physically Based Rendering,)
- linked with libsvm to solve for the SVM coefficients
- \[ \arg \max_{\alpha} \left\{ \sum \alpha_i - \sum \gamma_j \alpha_i \alpha_j K(x_i, x_j) \right\} \]
- Features, labelled by color distance to highest resolution, normalized so that labels are balanced, include:
  - Variance in Illuminance of the combined ray collection
  - Color value of the combined ray collection
  - Differences of the 3 XYZ color channels of the two sets of ray collections
  - Difference in variance in illuminance of the two sets of ray collections
  - Number of distinct primitives that our combined ray collection hit

Implementation
We trained our models on 4 images of 200x200 resolution. We experimented with different SVM parameters; in particular, data size and labelling thresholds were a big problem as there were a lot of support vectors.

Implementation-cont.
However, we obtained quite accurate results with the radial basis kernel.

Results
Here are some produced images and relevant data on our SVM models.

Future Work
- More features via better data interception
- Optimization: Ultimate goal is to make it a faster sampler
- Different labelling schemes

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