Adversarial Attacks on Black Box Video Classifiers: Leveraging the Power of Geometric Transformations







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Introduction

Black-box Adversarial Attack on Video Classifiers

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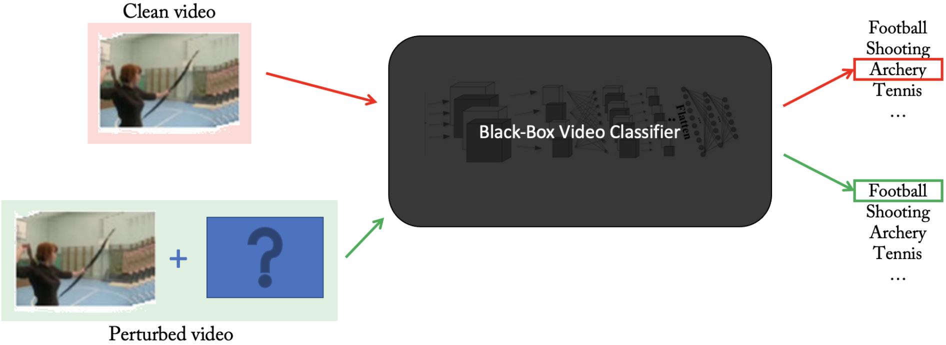

Black-box Adversarial Attack on Video Classifiers

- **Effective attacks:** Better gradient estimation is the key to query-based black-box attack.

(a) Illustration of White-box attack

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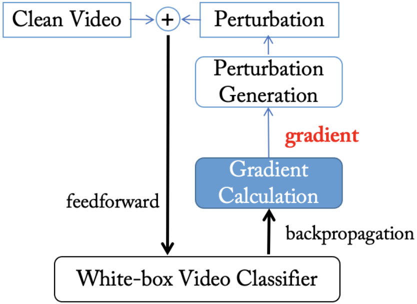
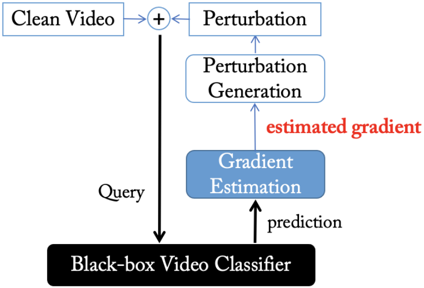


(a) Illustration of White-box attack



(b) Illustration of Black-box attack

Gradient Estimation

Gradient Estimation: Sampling Directions

- A simplified algorithm.
- How to sample π is important!

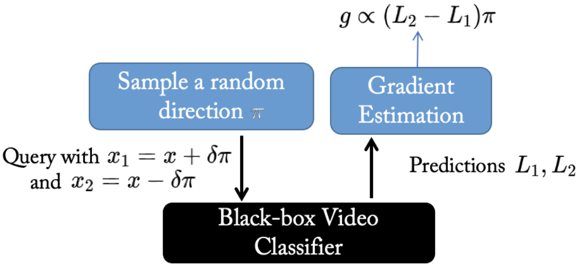


Figure 2: Gradient estimation for high dimensional function

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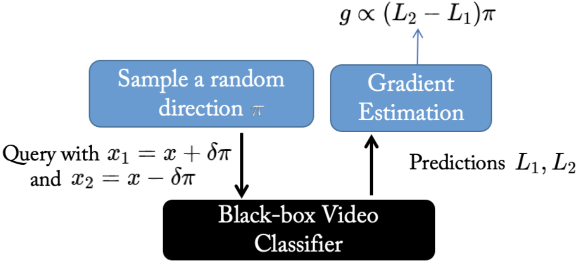

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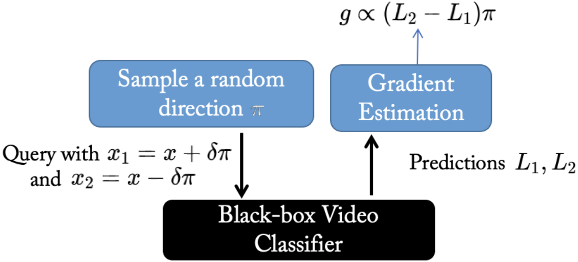
Gradient Estimation: Query-efficiency

- π is in high dimensional space $D = T \times H \times W \times C$, where T is the number of frames, H and W are the height and width of the frames, C is the number of channels.
- Higher dimensionality leads to more number of queries $\rightarrow$ becomes worse compared to query-based image attacks.
- **Goal:** Query-efficient query-based video attack!



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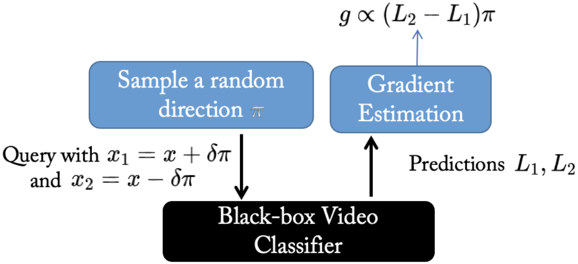

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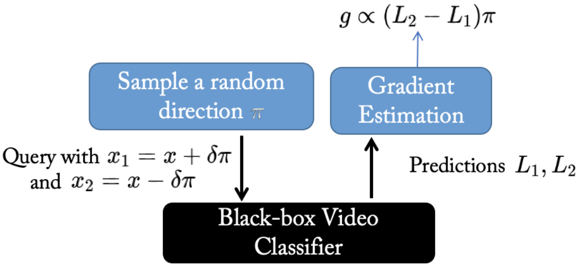

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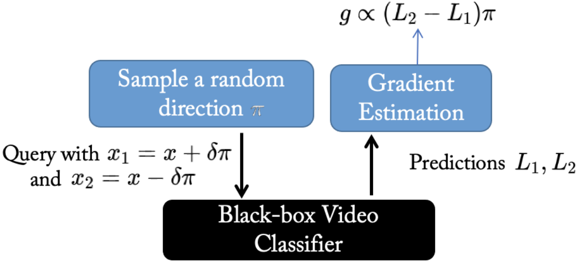
Motivation of Proposed Work

Motivation: Reduce the Search Space

- To estimate better gradient g.
- Sample π in a subspace (dimensionality reduction), which contains more effective π.
- Consider the intrinsic different between images and videos, i.e., the temporal dimension and aim to disrupt the motion context of videos.



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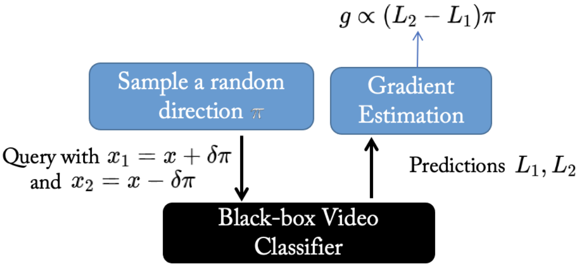

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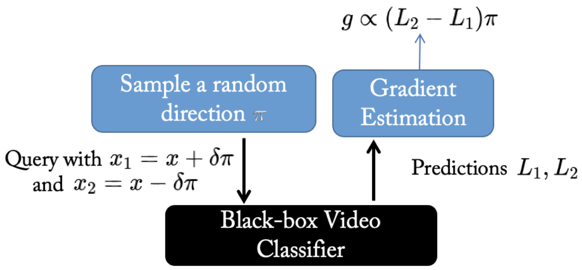

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Proposed Method:

GEOmetrically TRAnsformed Perturbations (GEO-TRAP)

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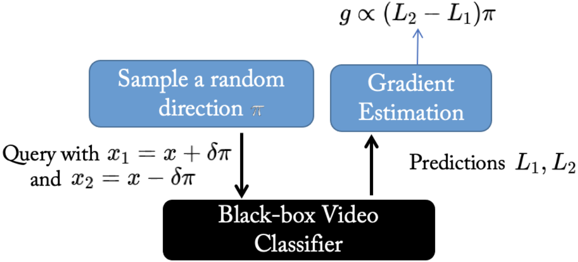
- Randomly sample $\boldsymbol{r}_{\text{frame}} \in \mathbb{R}^{H\times W\times C}$, then warp $\boldsymbol{r}_{\text{frame}}$ with T random geometric transformations to get $\boldsymbol{\pi} \in \mathbb{R}^{T\times H\times W\times C}$



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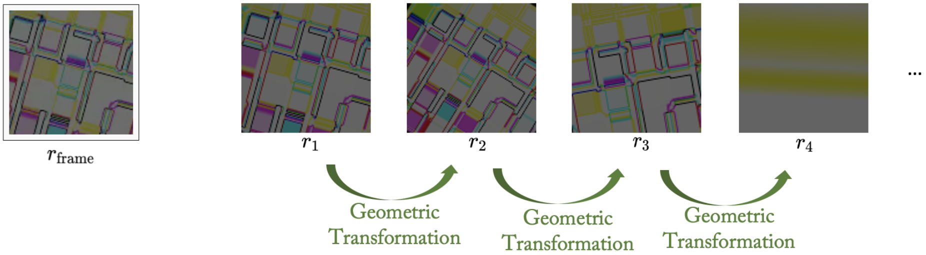
Proposed Method: GEO-TRAP

- **Dummy Illustration:** Warping random noise r_{frame} to create search directions for gradients



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Why does it work?

- Temporally structured perturbations.
  - Geometric progression in the temporal dimension.
- Assume the degrees of freedom of the geometric transformation is F, the dimensionality D is then reduced from $(T \times H \times W \times C)$ to $(H \times W \times C) + (T \times F)$ where, $F << T \times H \times W \times C$.
  - e.g. $F = 6$ for affine transformation.

Why GEO-TRAP works?

- Cosine similarity between the estimated $\boldsymbol{g}$ and the ground truth $\boldsymbol{g}^\star$, averaged over 1000 randomly chosen samples.
- **Takeaway:** GEO-TRAP estimates better gradients compared to baselines.

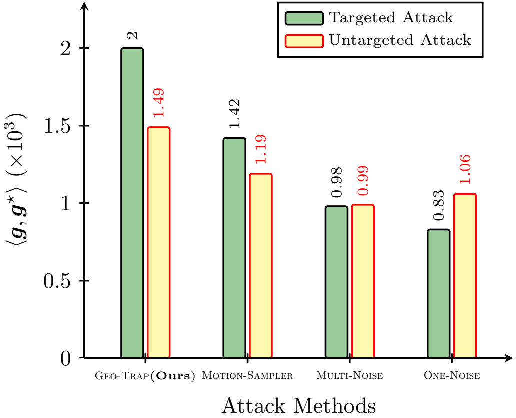
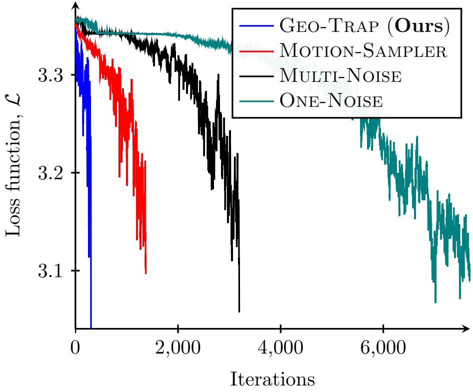


Figure 2: Measure the quality of estimated $\boldsymbol{g}$

Why GEO-TRAP works?

- **Better gradients** leads to quicker convergence, thus **fewer number of queries** required.



Experimental Result

Evaluation Metric:

- **Success Rates (SR):** total success rate of attack within query and perturbation budgets.
- **Average Number of Queries (ANQ):** the average total queries from attacks for all videos (including failed ones).

Datasets:

- **UCF-101**[1]: UCF-101 includes 13320 videos from 101 human action categories (e.g., applying lipstick, biking).
- **20BN-JESTER (Jester)**[2]: Jester includes 27 kinds of gesture videos recorded by crowd-sourced workers (e.g., sliding hand left, sliding two fingers right).

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- **Takeaway:** GEO-TRAP achieves the same or higher attack Success Rates (SR) compared to other methods, and requires fewer Average Number of Queries (ANQ).
- More results and analysis in the paper.

Table 1: GEO-TRAP demonstrates highly successful untargeted attacks with fewer queries.

Datasets	Methods	Black-box Video Classifiers							
		C3D		SlowFast		TPN		I3D	
		ANQ (↓)	SR (↑)	ANQ (↓)	SR (↑)	ANQ (↓)	SR (↑)	ANQ (↓)	SR (↑)
Jester	HEURISTICATTACK[3]	4699	99.0%	3572	98.1%	4679	82.0%	4248	98.1%
	MOTION-SAMPLER ATTACK[4]	4549	99.0%	1906	100%	6269	91.3%	3029	99.4%
	GEO-TRAP (**Ours**)	**1602**	**100%**	**521**	**100%**	**3315**	**92.4%**	**1599**	**100%**
UCF-101	HEURISTICATTACK	**5206**	70.2%	3507	87.2%	**6539**	71.8%	6949	84.7%
	MOTION-SAMPLER ATTACK	14336	81.6%	4673	97.2%	20369	75.8%	7400	94.4%
	GEO-TRAP (**Ours**)	11490	**86.2%**	**1547**	**98.8%**	17716	**76.1%**	**4887**	**97.4%**

[3] Zhipeng Wei et al. "Heuristic black-box adversarial attacks on video recognition models". *AAAI*. 2020.

[4] Hu Zhang et al. "Motion-Excited Sampler: Video Adversarial Attack with Sparked Prior". *ECCV*. 2020.

Conclusion

- We propose a new black-box video attack method, which parameterizes the video search space into an image search space and a geometric transformation parameter search space.
- With the reduced and temporally structured search space, we are able to achieve higher attack success rate with fewer queries.

Thank You!

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- **Paper link** → `https://arxiv.org/pdf/2110.01823.pdf`