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# Predicting cross-barrier communication disruption using adaptive Support Vector Machines

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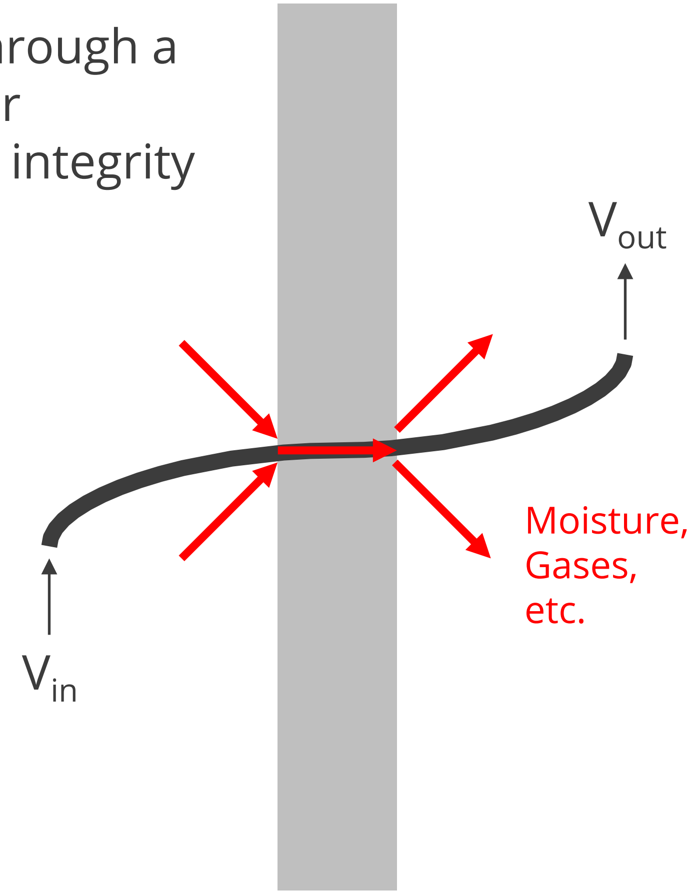
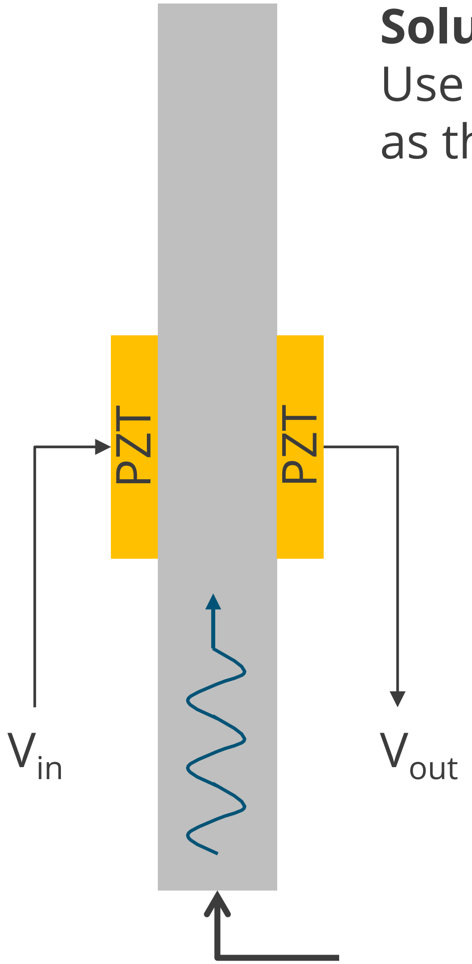
# Cross-Barrier Communication: Motivation

**Problem:**
Running wires through a protective barrier compromises its integrity




**Solution:**
Use the barrier itself as the data stream conduit




**Complication:**
The data stream is now susceptible to new sources of disruption (mechanical)

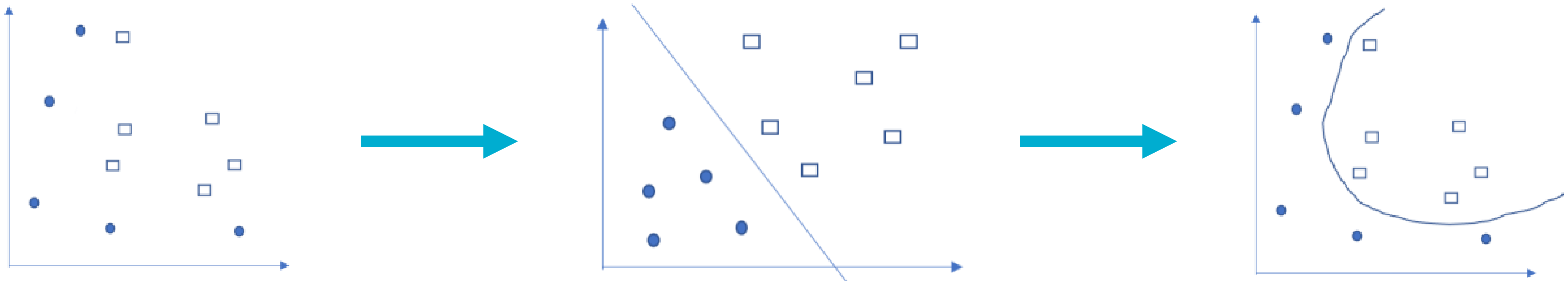
# Problem Description

- Assume mechanical shock can be modelled as decaying sine
- We are interested in identifying what kinds of shocks produce data disruption
  - Points towards a classification problem
- We are only interested in pass/fail
  - Points towards a binary classifier
- Physics model may be expensive to evaluate
  - Points towards an adaptive approach (sequential learning)

Chosen Classifier: (Adaptive) Support Vector Machines

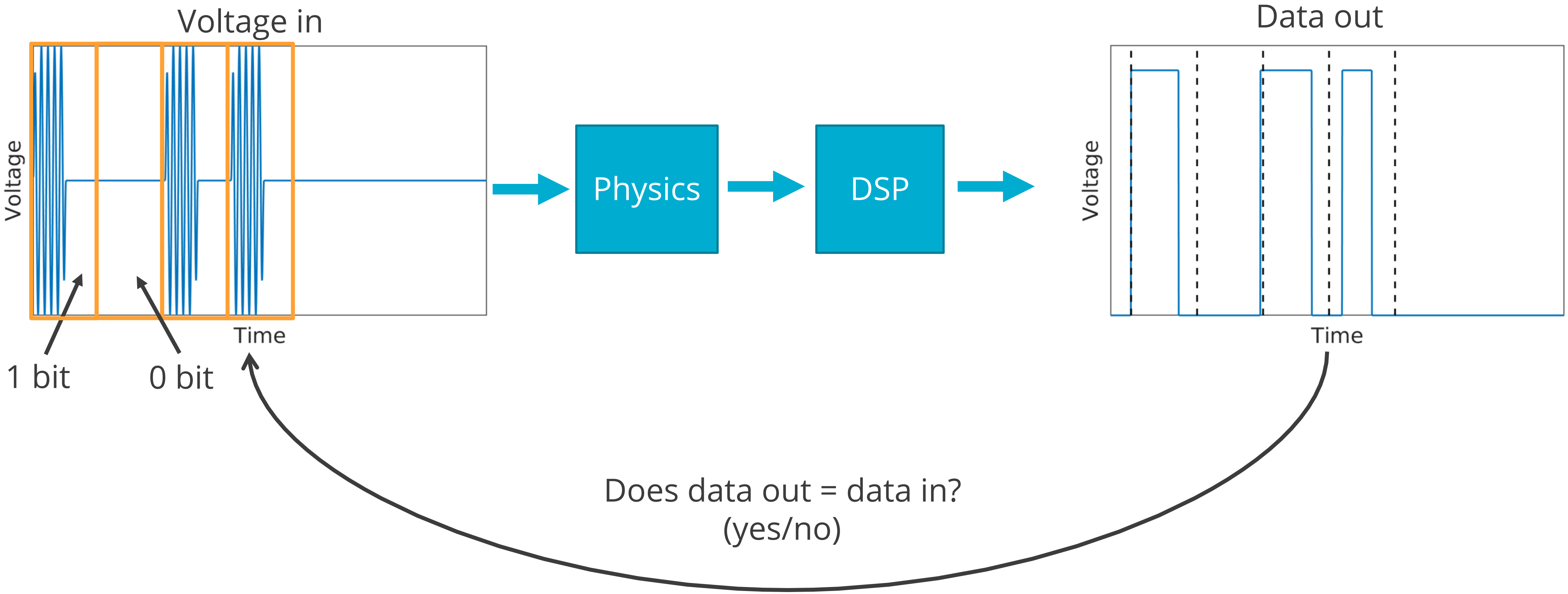
# SVMs and Adaptive SVMs

- Support Vector Machines (SVMs) seek the hypersurface that maximizes separation of pre-classified samples (supervised)
- In simplest case, data is linearly separable
- When data is not linearly separable, we can map the data to a space where it is linearly separable

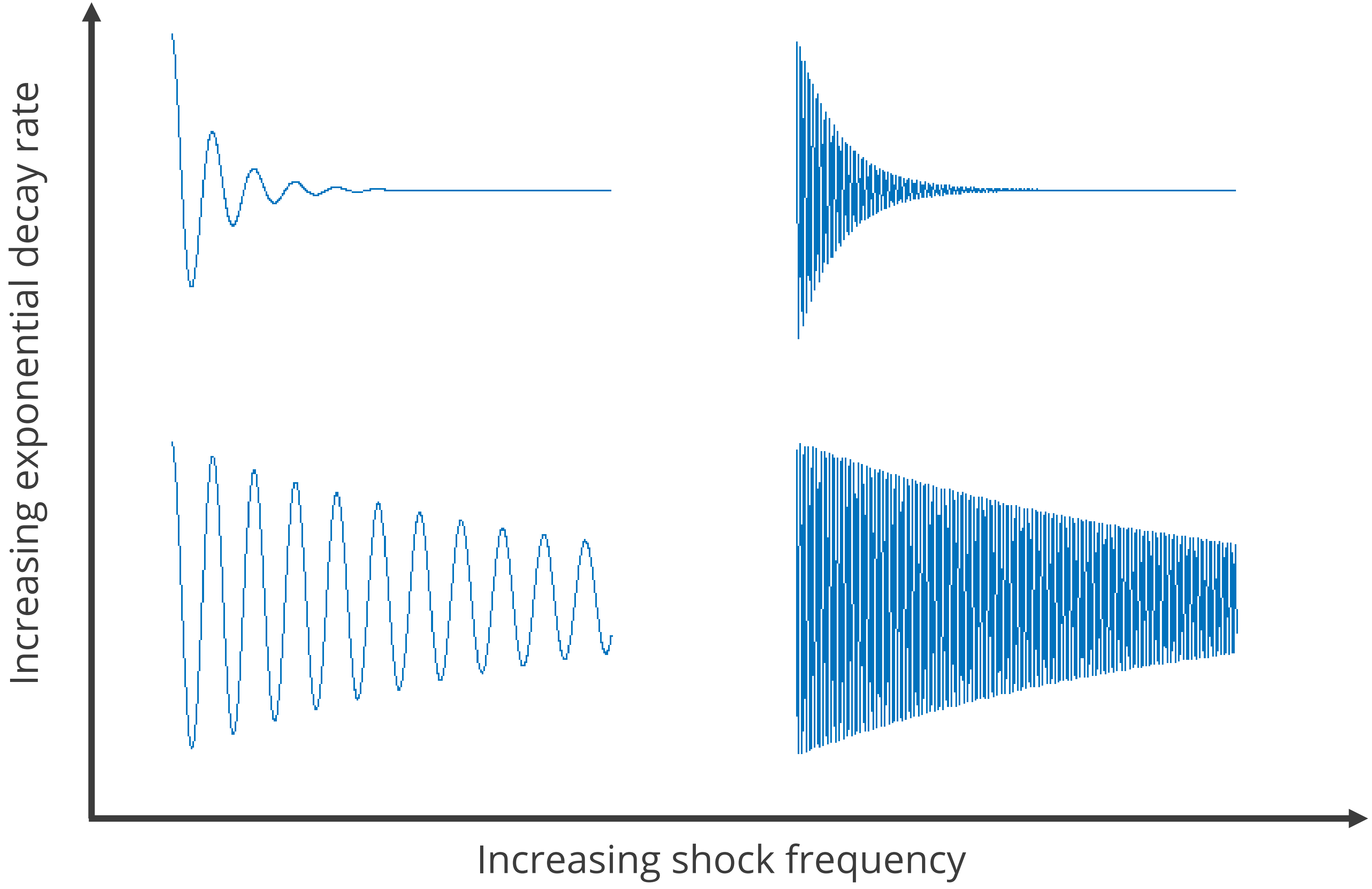


- SVMs provide a closed-form expression for the hypersurface, a convex optimization problem for training, resiliency to the curse of dimensionality, and straightforward extensions to adaptive strategies

# Problem Workflow

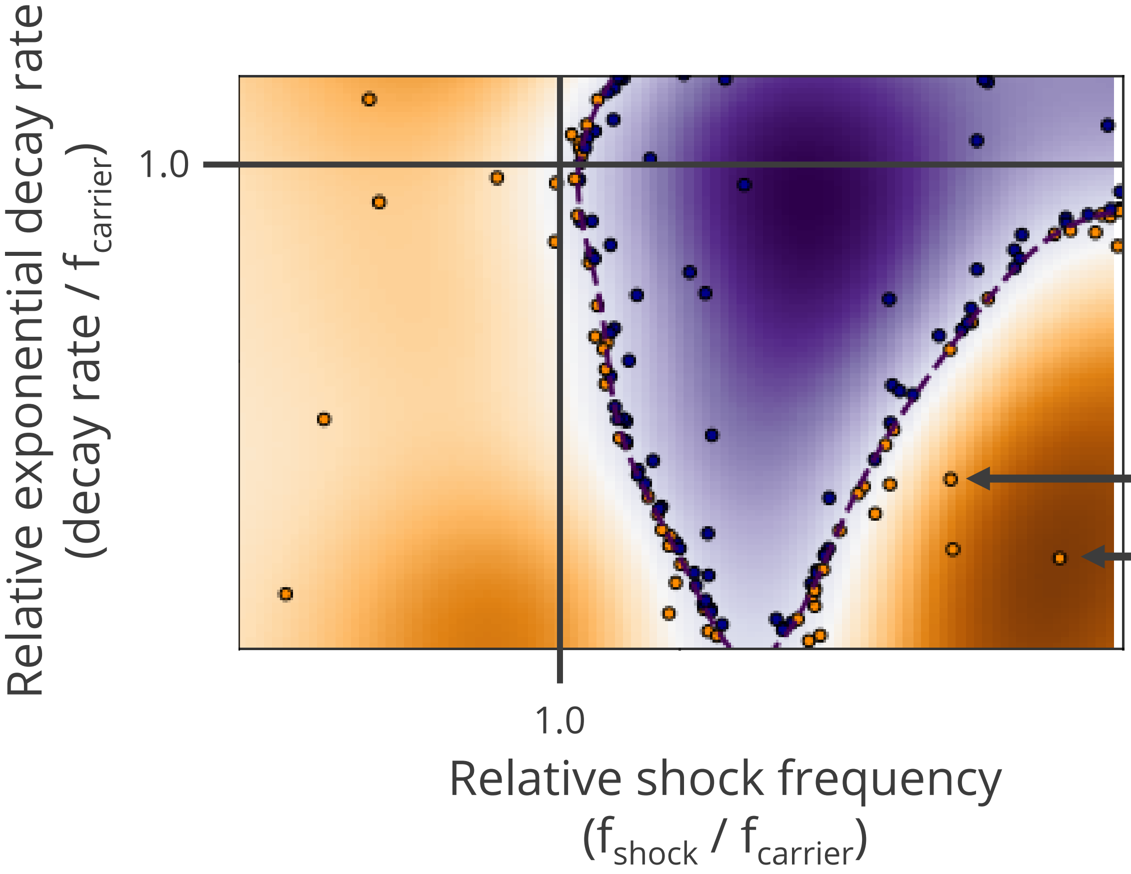


# Input parameters




In addition, explored several different levels of shock amplitude

# Low shock amplitude



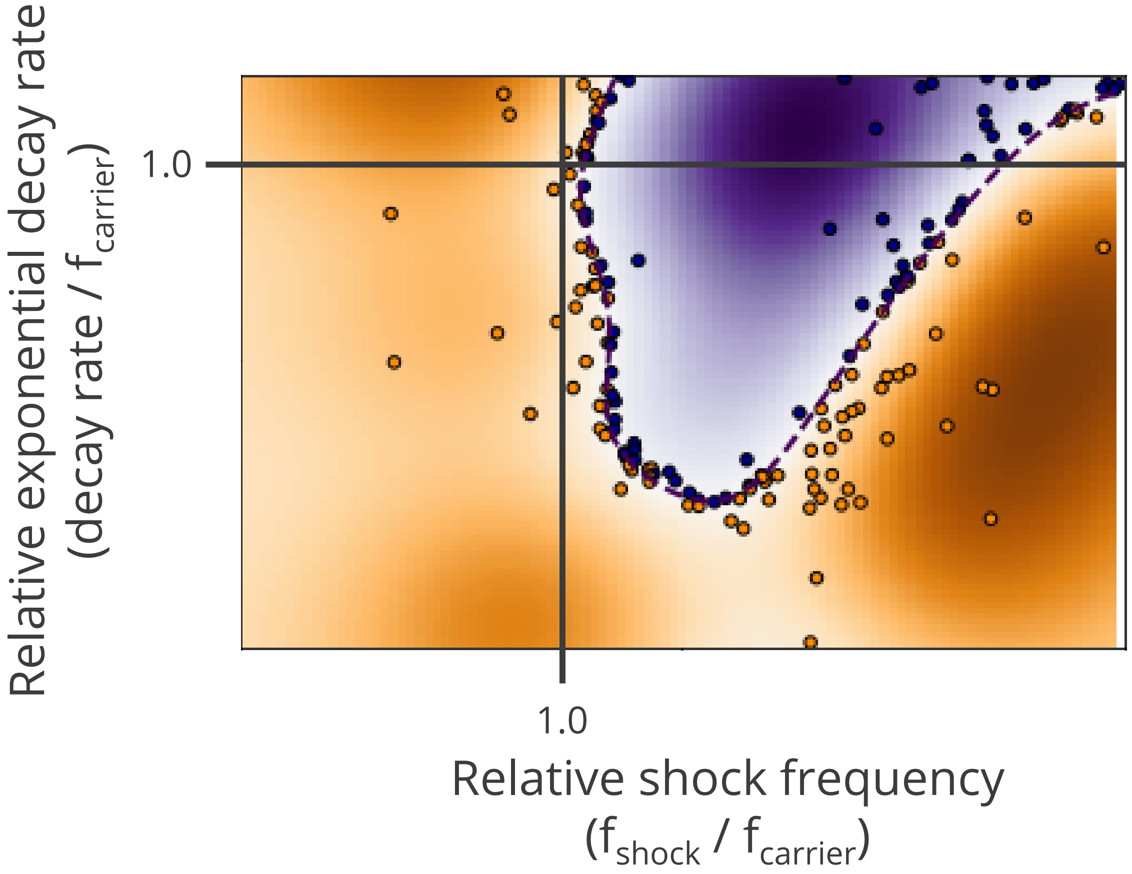

Blue = no data loss

Orange = data loss

Hypersurface separates the two

Boundary is estimated from a small, adaptively-determined training set

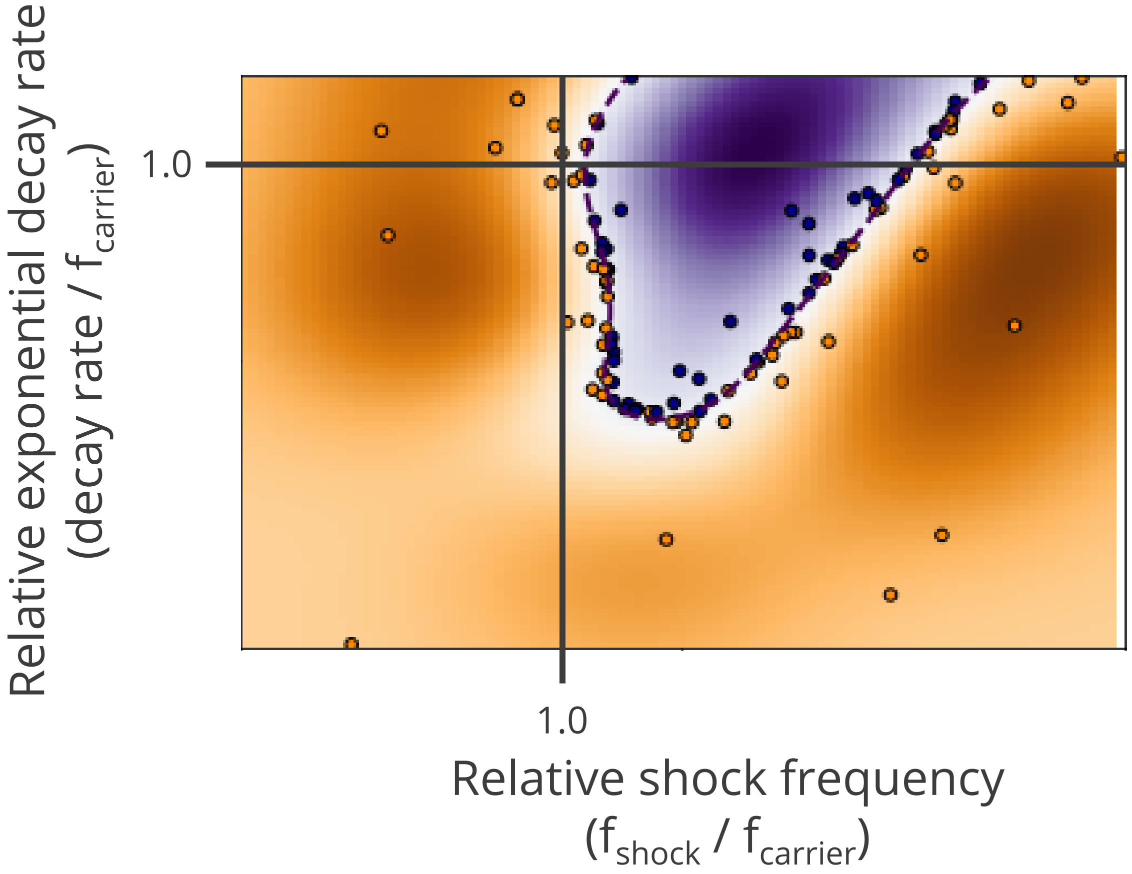
# Medium shock amplitude




Blue = no data loss

Orange = data loss

# Large shock amplitude

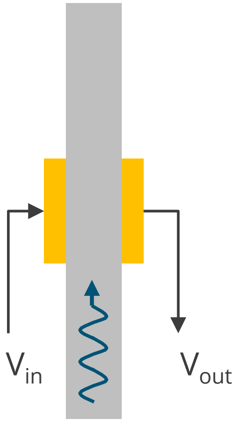



Blue = no data loss

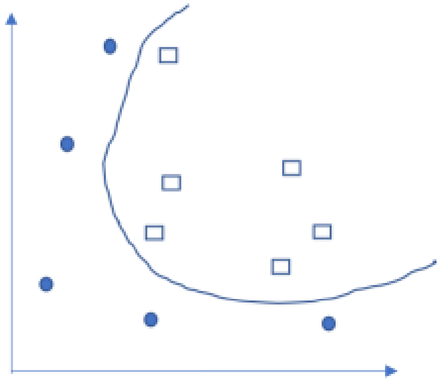
Orange = data loss

# Summary

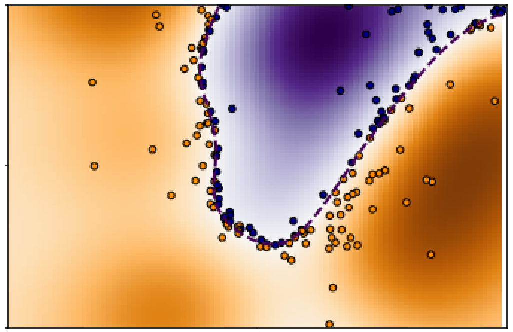
- Cross-barrier communication can maintain integrity of a protective barrier
  - Exposes the communication channel to new sources of disruption




- We formulated this disruption risk as a classification problem
  - Used adaptive SVMs to explore the space



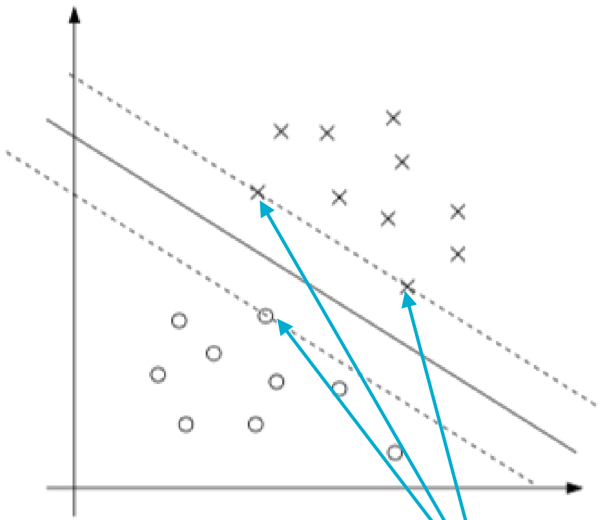
- SVMs identified sets of shock parameters that lead to data disruption
  - Points towards regions that need to be protected against or designed around



# Backups

# Quick Overview of SVMs

Credit: W. Aquino



Support vectors

- The SVM training problem in primal form

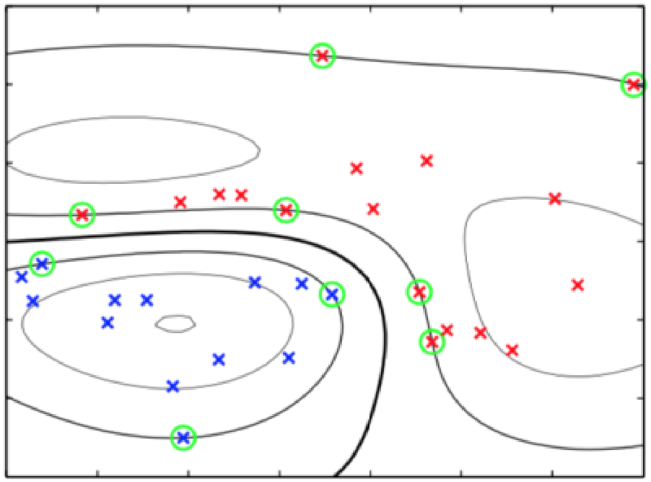
$$\underset{\boldsymbol{w},w_0}{\text{minimize}} \quad \frac{1}{2}\|\boldsymbol{w}\|^2$$
$$\text{s.t.} \quad y_i\left(\boldsymbol{w}^T\boldsymbol{x}_i + w_0\right) \geq 1 \quad i = 1, ..., m$$

- General Formulation with Basis Functions

$$\underset{\boldsymbol{w},w_0}{\text{minimize}} \quad \frac{1}{2}\|\boldsymbol{w}\|^2$$
$$\text{s.t.} \quad y_i\left(\boldsymbol{w}^T\boldsymbol{\phi}(x_i) + w_0\right) \geq 1 \quad i = 1, ..., m$$

- Kernels:

$$K(\boldsymbol{x},\boldsymbol{x}') := \langle\boldsymbol{\phi}(\boldsymbol{x}),\boldsymbol{\phi}(\boldsymbol{x}')\rangle$$



Decision contours using Gaussian Kernel

# Classification vs Regression

Credit: W. Aquino

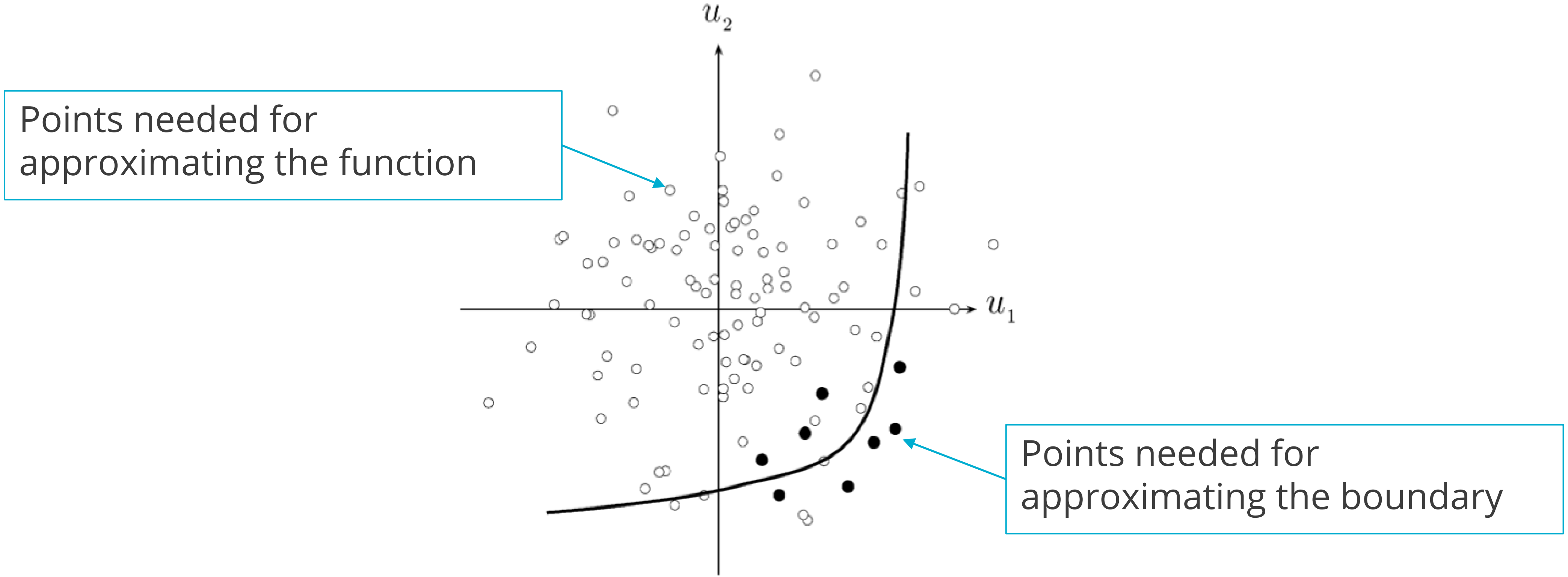
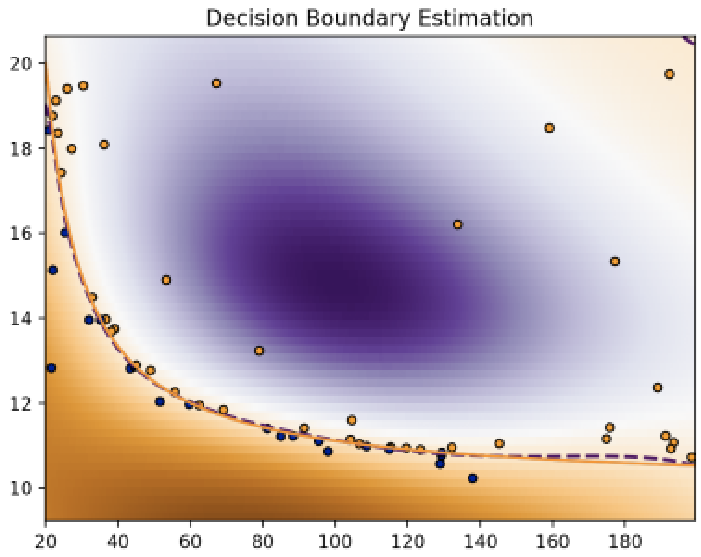



Fig. 6. The sampling for approximating the limit state function (black circles) differs from that aimed at approximating the performance function (white circles).

Credit: J.E. Hurtado, doi: 10.1016/j.strusafe.2003.05.002

# Algorithm For Decision Boundary Detection

Credit: W. Aquino




- Form the background set $X_b$ by drawing $M$ background samples $x_j \in X$ using a uniform distribution.
- Add the first $n$ samples in $X_b$ to the training set $X_{tr}$ and remove from $X_b$.
- Evaluate the training samples using the physics model as $g(x_j), x_j \in X_{tr}$. If there is at least one sample in each of $\mathcal{D}^+$ and $\mathcal{D}^-$ continue.
- Otherwise, continue drawing samples from $X_b$ and adding to the training set without replacement until there is at least one positive and one negative sample.
- While not converged and background samples are available,
  1. Train a SVM using the current training set.
  2. Evaluate the decision function, $f(x)$, from the current SVM on the background set.
  3. Find the two points that are closest to the boundary on the + and - sides and denote as $x_k^+, x_k^-$.
  4. Evaluate the latter two points using the physics-based function as $g(x_k^+)$ and $g(x_k^-)$.
  5. Add these points to the training set and remove from the background set.
  6. Compute convergence metric.