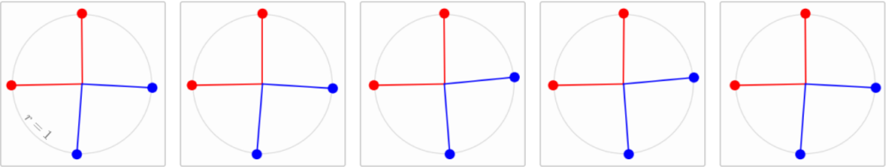
ORGANIZATION OF CORRELATED AND ANTICORRELATED FEATURES

For our initial investigation, we simply train a number of small toy models with correlated and anti-correlated features and observe what happens. To make this easy to study, we limit ourselves to the $m = 2$ case where we can explicitly visualize the weights as points in 2D space. In general, such solutions can be understood as a collection of points on a unit circle. To make solutions easy to compare, we rotate and flip solutions to align with each other.

Models prefer to represent correlated features in orthogonal dimensions.

We train several models with 2 sets of 2 correlated features (n=4 total) and a m=2 hidden dimensions. We then visualize the weight column for each feature. For ease of comparison, we rotate and flip solutions to have a consistent orientation.

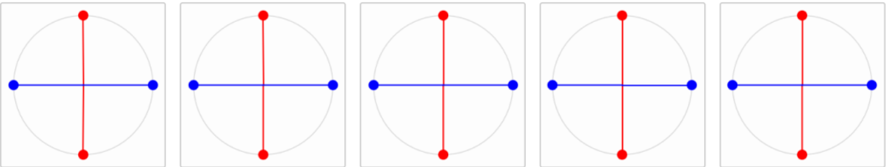


●● and ●● denote **correlated** feature sets.

Correlated feature sets are constructed by having them always co-occur (ie. be zero or not) at the same time.

Models prefer to represent anticorrelated features in opposite directions.

We train several models with 2 sets of 2 anticorrelated features (n=4 total) and a m=2 hidden dimensions. We then visualize the weight column for each feature. For ease of comparison, we rotate and flip solutions to have a consistent orientation.

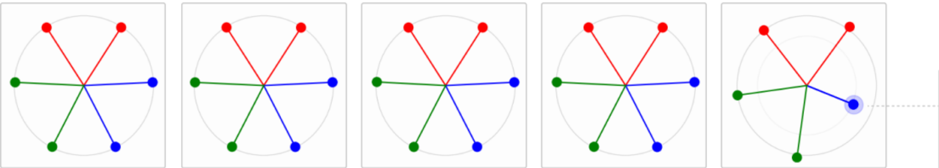


●● and ●● denote **anticorrelated** feature sets.

Anticorrelated feature sets are constructed by having them never co-occur (ie. be zero or not) at the same time.

Models prefer to arrange correlated features side by side if they can't be orthogonal.

We train several models with 3 sets of 2 correlated features (n=6 total) and a m=2 hidden dimensions. We then visualize the weight column for each feature. For ease of comparison, we rotate and flip solutions to have a consistent orientation. (Note that models will not embed 6 independent features as a hexagon like this.)



●●, ●●, and ●● denote **correlated** feature sets.

Sometimes correlated feature sets "collapse". In this case it's an optimization failure, but we'll return to it shortly as an important phennomenon.

LOCAL ALMOST-ORTHOGONAL BASES

It turns out that the tendency of models to arrange correlated features to be orthogonal is actually quite a strong phenomenon. In particular, for larger models, it seems to generate a kind of "local almost-orthogonal basis" where, even though the model as a whole is in superposition, the correlated feature sets considered in isolation are (nearly) orthogonal and can be understood as having very little superposition.

To investigate this, we train a larger model with two sets of correlated features and visualize W^TW.