Consider a classifier hypothesis set of squares. A single hypothesis \( h \) is a square with a fixed size and location. Four example hypotheses are shown.

And here is examples of \( h \) that will help shatter a set of three data points.

For each data set:
- What is a set of 4 shatterable points ("none" is a possible answer)
- What is the VC dimension?

Example 1:

Example 2:
Example 3:

Four points: Either NONE or could argue B, C, E, F (B is SLIGHTLY lower than C) (A, C, E, F)
VC: 3 (or 4 if you think B is sufficiently lower than C)

Consider the following HMM. It uses a thermometer to attempt to predict the weather.

We begin with the following estimate for our HMM parameters:
\[ \Pi_{\text{snow}} = 0.2 \quad \Pi_{\text{rain}} = 0.3 \quad \Pi_{\text{sunny}} = 0.3 \quad \Pi_{\text{cloudy}} = 0.2 \]

\( \phi_{o,i}: \)

<table>
<thead>
<tr>
<th></th>
<th>Cold</th>
<th>Mild</th>
<th>Hot</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snow</td>
<td>0.8</td>
<td>0.2</td>
<td>0</td>
</tr>
<tr>
<td>Rain</td>
<td>0.5</td>
<td>0.3</td>
<td>0.2</td>
</tr>
<tr>
<td>Sunny</td>
<td>0</td>
<td>0.3</td>
<td>0.7</td>
</tr>
<tr>
<td>Cloudy</td>
<td>0.2</td>
<td>0.7</td>
<td>0.1</td>
</tr>
</tbody>
</table>

(We COULD actually learn a Gaussian function for the temperature for each state. Here, we'll just do a discrete probability table.)
We receive a new sequence of temperatures and wish to update our HMM parameters.

Sequence:
Cold  Cold  Hot  Mild  Hot

Correct alpha values are in black. Made-up alpha values are in color parentheses. You will have to find the real values below. You can use the made-up value in calculating $S_t$ values further below.

\[
\alpha_t(i)
\]

<table>
<thead>
<tr>
<th>t</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snow</td>
<td>?? (.11)</td>
<td>.08</td>
<td>0</td>
<td>.00011</td>
<td>0</td>
</tr>
<tr>
<td>Rain</td>
<td>0.15</td>
<td>?? (.04)</td>
<td>.0082</td>
<td>.0017</td>
<td>.00049</td>
</tr>
<tr>
<td>Sunny</td>
<td>?? (.08)</td>
<td>0</td>
<td>.0056</td>
<td>?? (.0033)</td>
<td>.0020</td>
</tr>
<tr>
<td>Cloudy</td>
<td>0.04</td>
<td>.027</td>
<td>?? (.0044)</td>
<td>.0053</td>
<td>.00030</td>
</tr>
</tbody>
</table>

Correct beta values are in black. Made-up beta values are in color parentheses. You will have to find the real values below. You can use the made-up value in calculating $S_t$ values further below.

\[
\beta_t(i)
\]

<table>
<thead>
<tr>
<th>t</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snow</td>
<td>.0067</td>
<td>.0062</td>
<td>.13</td>
<td>.05</td>
</tr>
<tr>
<td>Rain</td>
<td>.0097</td>
<td>?? (.011)</td>
<td>.13</td>
<td>?? (.08)</td>
</tr>
<tr>
<td>Sunny</td>
<td>.0028</td>
<td>.087</td>
<td>?? (.11)</td>
<td>.52</td>
</tr>
<tr>
<td>Cloudy</td>
<td>.0062</td>
<td>.047</td>
<td>.121</td>
<td>?? (.11)</td>
</tr>
</tbody>
</table>

Find the missing values in the tables above.

\[
\alpha_1(Snow) = 0.2 \times 0.8 = \textcolor{red}{0.16}
\]
\[
\alpha_3(Cloudy) = 0.1 \times (0.024 + 0.02 + 0.0081) = 0.1 \times 0.052 = \textcolor{red}{0.0052}
\]
\[
\beta_4(Rain) = (0.1 + 0.05) = \textcolor{red}{0.15}
\]
What are the values:

Corrected Dec 12:

\[
S_2(\text{cloudy}) = \frac{0.027 \times 0.047}{0.00127 + 0.00221} = 0.58
\]

\[
S_3(\text{snow,sunny})
\]

\[
S_1(\text{rain})
\]

Now let us presume the following S values (these are made-up values):

\[
\begin{array}{c|ccccc}
 t & 1 & 2 & 3 & 4 & 5 \\
\hline
\text{Snow} & 0.3 & 0.3 & 0.1 & 0.2 & 0.1 \\
\text{Rain} & 0.5 & 0.4 & 0.3 & 0.3 & 0.2 \\
\text{Sunny} & 0.1 & 0.1 & 0.3 & 0.1 & 0.4 \\
\text{Cloudy} & 0.1 & 0.2 & 0.3 & 0.4 & 0.3 \\
\end{array}
\]

\[
\begin{array}{c|cccc}
 t & 1 & 2 & 3 & 4 \\
\hline
\text{Rain, Cloudy} & .1 & .4 & .3 & .2 \\
\text{Sunny, Rain} & 0 & 0 & 0 & 0 \\
\end{array}
\]

\[
\Pi_{\text{rain}} \quad \Pi_{\text{cloudy}}
\]

\[
A_{\text{rain,cloudy}} \quad A_{\text{sunny, rain}} = 0
\]

\[
\phi_{\text{hot, rain}} \quad \phi_{\text{mild, sunny}} = \frac{0.1}{0.1 + 0.3 + 0.1 + 0.4} = \frac{0.1}{1} = 0.1
\]