## **3. X‑Learner (Cross Approach)**

**How it works:**

1. Start like T‑Learner — build two models.
2. Each group then **guesses what would’ve happened if they were in the other group**.  
   * Treated customers compare their actual results to what the “control model” predicts.
   * Control customers compare their actual results to what the “treated model” predicts.
3. Combine the two perspectives, weighted by how likely people like them usually are to get treated.

**4. U‑Learner (Uplift Learner)**

### **Step‑by‑Step Explanation**

1. **Predict what’s “normal”**
   * First, the model learns what customers are likely to do naturally — even without the campaign.
   * Example: *“Based on age, income, and past behavior, this customer usually has a 20% chance to buy anyway.”*
2. **Check what actually happened**
   * Then we compare the actual outcome to this natural expectation.
   * Example: *“The customer actually bought — that’s higher than the 20% we expected.”*
3. **Adjust for fairness**
   * Not everyone had the same chance of being in the campaign. Some groups are more likely to get treated.
   * So we adjust for how “surprising” it was that they got treated.
4. **Measure the real campaign effect**
   * The leftover difference, after adjusting for normal behavior and treatment bias, is the true uplift.

5.  **R‑Learner (Residual Learner)**

### **Step‑by‑Step Explanation**

1. **Remove the obvious**
   * First, take away the part of the outcome that can already be explained by normal customer behavior.
   * Example: *“We know from their profile they’d usually have a 30% chance of buying. Let’s subtract that.”*
2. **Remove the treatment bias**
   * Next, take away the part that just comes from how likely they were to get the campaign in the first place.
   * Example: *“This group is very likely to receive the campaign, so we shouldn’t give the campaign too much credit.”*
3. **Look at what’s left (the residuals)**
   * Now, only the unexplained part remains — the true effect of treatment.
4. **Learn the uplift pattern**
   * Finally, the model looks at many customers’ residuals to learn how features (like age, income, product history) affect the campaign’s impact.

## **6. Causal Trees / Causal Forests**

**How it works:**

1. Split customers into smaller groups based on features (like age, income, history).
2. For each group, compare results between treated and untreated.
3. The difference shows which groups are most persuadable.