Multi-Stage Stratified Sampling for the Design of Large Scale Biometric Systems

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Problem

• How to create a set of biometric samples for research?
  • How many subjects to include in a sample?
  • How are subjects chosen?

• Performance prediction requires adequate population samples too.
  • Convenience sampling introduces strong bias.
  • Alternative sampling methods have cost and practicality implications for data collections.
Stratification Benefits

• Stratification - the process of dividing population into homogeneous, mutually exclusive subgroups.

• Multi-stage stratified sampling design increases “trustworthiness” of match rate estimates
  • Lower costs and smaller performance prediction errors.

• We address the following specific questions:

  1. How can a researcher use existing large datasets to generate stratified samples for the purpose of biometric performance prediction?
  2. What are practical benefits of stratification?
Our Approach

- The process:
  - We investigate the Performance Prediction phase.
  - Sample size estimation approach for Rank 1 identification rate estimation.

Sample Size Estimation

Grouping Data by Covariate

Get Sample

Pre-processing

Matching / Decision Making

Feature Extraction

Deployed Biometric System

Performance Prediction

Face Images

Our Approach
• Stratified Sampling first partitions the population into $L$ available groups (e.g. males, females).
  • Within each group, a sample is created by taking an independent simple random sample.

• Goal: Participants within each group are as similar as possible.
  • Individual stratum variances are minimized.

• What is the criteria for effective grouping?
  • There should be clear differences in match rates between strata.
    • May be algorithm dependent!
  • Strata based on eye color, facial hair or hair color do not exhibit this.
  • In face recognition, age group, ethnicity and gender could be used as strata.
Stratified and Simple Random Sampling: Difference

• *Simple Random Sampling* takes a sample from a population in a way so that each sample has the same chance of being selected.

• In *stratified random sampling*, the population is first separated into non-overlapping strata. A sample is created by simple random sampling from each stratum.

• *Sample size from each strata may differ.*
Intuition: How tall are NBA players?

- # Players: 434; Mean height: 79.04in; Variance: 12.9 in^2
- How many players must be sampled to estimate the average height to within one inch?
- Grouping the players by position reduces variance
  - 5.94 in.^2 (guards), 2.32 in.^2 (forwards), 1.85 in.^2 (centers)
- Simple random sampling: 47 observations.
- Stratified sampling: 13 (optimally allocated) observations.
- A stratified sample of 7 guards, 4 forwards, and 2 centers selected from any NBA season will yield an estimate of the mean height from that season, within an inch, 95% of the time.
Large Face Data Sets

- In large data sets, the number of false matches tends to increase.
  - Imposter score correlations close to 0 within each cluster helps reduce the FMR.
- We investigated imposter score correlations within the strata (e.g. African American females, Caucasian males).
  - Pinellas County Sherriff’s Office data set.
    - Most of the subjects are white males.
    - 2.5K each for male/female and black/white demographics.
  - Experiment: FaceVACS 8.6.0, 10,000x10,000 match scores.
Genuine/Imposter Score Distributions

- Score distributions change with demographic information.
  - Black female similarity scores exhibit a larger variance.
    - Added uncertainty will have a significant impact in matching.
If the variation in similarity scores among black females is reduced, and if no imposter score correlation existed, black females would become more identifiable.
Impostor Score Correlation

Imposter Scores of 2 Black Females

- The correlation coefficient above is **0.595**.
- Similarity scores between different, unrelated subjects exhibit almost a linear relationship.
- The matcher has difficulties differentiating between the black females.

Imposter Scores of 2 White Females

- The correlation coefficient here is **-0.006** (no relationship).
- This is desirable because the matcher is having a much easier time differentiating the individuals in these images.
Stratified Sampling, Correlation, Large Samples

- Stratified sampling assigns a higher “weight” to cohorts that are seen to cause difficulties in facial recognition.

- Correlations among imposter scores of black females likely due to insufficient training with black female samples [Klare et al.]

Higher Variance

Lower Variance
**Match Results**

*Table: Genuine Accept Rates (GAR) at a fixed False Accept Rate of 0.01%*

<table>
<thead>
<tr>
<th>Demographic</th>
<th>Black Females</th>
<th>Black Males</th>
<th>White Females</th>
<th>White Males</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>GAR</strong></td>
<td>0.8048</td>
<td>0.87</td>
<td>0.8684</td>
<td>0.916</td>
<td>0.853</td>
</tr>
</tbody>
</table>

**Grouped by Gender**

<table>
<thead>
<tr>
<th>Gender</th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>94.4%</td>
<td>89.5%</td>
</tr>
</tbody>
</table>

**Grouped by Ethnicity**

<table>
<thead>
<tr>
<th>Ethnicity</th>
<th>Black</th>
<th>White</th>
<th>Hispanic</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>88.7%</td>
<td>94.4%</td>
<td>95.7%</td>
</tr>
</tbody>
</table>

**Grouped by Age**

<table>
<thead>
<tr>
<th>Age Group</th>
<th>18-30</th>
<th>30-50</th>
<th>50-70</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>91.7%</td>
<td>94.6%</td>
<td>94.4%</td>
</tr>
</tbody>
</table>

- Large difference in GAR between black females and white males.
- *Face Recognition Performance: Role of Demographic Information [Klare et al.]*
  - There seem to be extra interactions with gender and ethnicity that increase differences in match rates.
- Dynamic face matcher selection.
Sample Size Equations

- $B$ represents a chosen bound.
- $N (N_k)$ is overall sample (strata) size.
- $p (p_k)$ is the GAR at FAR 0.01%.

### Stratified Random Sampling

$$n = \frac{4 \left( \sum_{k=1}^{L} N_k \sqrt{p_k (1 - p_k)} \right)^2}{N^2 B^2 + 4 \sum_{i=1}^{L} N_i p_i (1 - p_i)}$$

### Simple Random Sampling

$$n = \frac{4 Np (1 - p)}{(N - 1) B^2 + 4 p (1 - p)}$$
Data Stratification

Table: Allocation of the sample based on Stratification

<table>
<thead>
<tr>
<th></th>
<th>Black Female</th>
<th>Black Male</th>
<th>White Female</th>
<th>White Male</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stratified</td>
<td>~30%</td>
<td>~25%</td>
<td>~25%</td>
<td>~20%</td>
</tr>
</tbody>
</table>

- Stratified sampling, using the 4 cohorts of interest, now allows for 230 fewer tests to estimate performance within 1%.
- An added bonus:
  - The next collection may emphasize the sampling of black females, the most troublesome cohort.

Note: The error bound for the plot above ranges from 0.9% to 1%.
Results

- The total sample sizes below were obtained using an error bound of 1%

**Simple Random Sampling**
- Total Size: 3341
  - Allocation:
    - 843 black females
    - 834 black males
    - 842 white females
    - 822 white males
  - Estimated GAR of 85.3% at an FMR of 0.01%.

**Stratified Random Sampling**
- Total Size: 3109
  - Allocation:
    - 933 black females
    - 777 black males
    - 777 white females
    - 622 white males
  - Estimated GAR of 85.3% at an FMR of 0.01%.

- Stratified random sampling achieved the same performance using 232 fewer subjects.
Data Extrapolation

- The total sample sizes below were obtained using an **error bound of 1%**.
- Differences when predicting a **population of one billion**. From previous studies, we are assuming a GAR of 85.3% at .01% FMR.

### SRS vs. Stratified Comparison

<table>
<thead>
<tr>
<th>Bound</th>
<th>Required Sample Size</th>
<th>SRS</th>
<th>Stratified</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>5,016</td>
<td>4,544</td>
<td>472</td>
</tr>
<tr>
<td>0.012</td>
<td>1,363</td>
<td>1,136</td>
<td>234</td>
</tr>
</tbody>
</table>

**Difference: 472**

### Allocation for Stratified Sampling

- **Black Females**: 909
- **White Females**: 1,363
- **Black Males**: 1,136
- **White Males**: 1,363
Data Extrapolation

- Now, we calculate the necessary sample size using an error bound of 0.01%.
- How many samples from a population of 1 billion would we need to estimate the GAR at 0.01% FMR to within 0.0001?

### Required Sample Size

<table>
<thead>
<tr>
<th>Bound</th>
<th>SRS</th>
<th>Stratified</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00008</td>
<td>47,760,886</td>
<td>43,430,444</td>
</tr>
<tr>
<td>Difference: 4,330,442</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Allocation for Stratified Sampling

- **Black Females**: 13,029,133
- **White Females**: 10,857,611
- **Black Males**: 8,686,089
- **White Males**: 6,690,607
Sample Size Reduction

- Stratified sampling requires around 10% fewer subjects to achieve the same performance estimate, regardless of the chosen error bound.
- In general, the choice of error bound will not have an impact on the sample size reduction due to stratification.
The Effect of Errors in Stratification

- In a simulation, 10% and 33% of African American population was reclassified as white and vice versa.

Simulate the effects of an incorrect classification by an algorithm or experimenter.

- Results (baseline is the leftmost table):

<table>
<thead>
<tr>
<th>GAR at .01% FMR (no errors)</th>
<th>GAR at .01% FMR (10% errors)</th>
<th>33% errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Black</td>
<td>White</td>
<td>Black</td>
</tr>
<tr>
<td>83.3 %</td>
<td>89.02 %</td>
<td>83.4 %</td>
</tr>
</tbody>
</table>

Differences:

<table>
<thead>
<tr>
<th>Black</th>
<th>White</th>
</tr>
</thead>
<tbody>
<tr>
<td>+0.1 %</td>
<td>-0.76%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>BLACK</th>
<th>WHITE</th>
</tr>
</thead>
<tbody>
<tr>
<td>+1.0 %</td>
<td>-2.96%</td>
</tr>
</tbody>
</table>
Summary

• Applied a stratified sampling design to face recognition. Approach offers savings in performance prediction for large systems. Offers guidance for performance prediction from existing collections.

• Unbiased performance predictions from a stratified sample. Given valid assumptions, performance predictions are accurate. The reward comes from the ability to allocate the sample.

• Investigated the effect of errors in demographic information. The strata seem robust to small strata misclassification.

• Should be extended to other biometric modalities. The role of matching algorithms.