SAS® GLOBAL FORUM 2017

April 2 – 5 | Orlando, FL

Estimation of Student Growth Percentiles using SAS procedures

USERS PROGRAM

Estimation of Student Growth Percentiles using SAS procedures

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ABSTRACT

Student Growth Percentiles (SGP) is one of the most widely-used score metrics for measuring a student's academic growth. Using longitudinal data, SGP describes a student's growth as the relative standing among students who had a similar level of academic achievement in previous years. Although there have been introduced several models for SGP estimation and some models was implemented with R, no studies have yet described these procedures using SAS®. Thus, this research describes various types of SGP models and demonstrates how practitioners can use the procedures in SAS® to fit these models. Specifically, this study covers three types of statistical models for SGP: (1) quantile regression-based model, (2) conditional cumulative density function-based model, and (3) latent multivariable-based model. Each of the three models partly employs procedures in SAS®, such as PROC QUANTREG, or PROC IRT, for its computation. The program code will be illustrated using a simulated longitudinal dataset over two consecutive years, which is generated by SAS/IML®. In addition, the interpretation of the estimation results and the advantages and disadvantages of implementing these three approaches in SAS® will be discussed.

MODELS

- **QUANTILE REGRESSION (QR)-BASED SGP**

The SGP for an individual with both current year score x and prior year score y, $g(x|y)$, is determined as the midpoint between the two ranks of the nearest conditional quantiles given y.

$$g(x|y) = \frac{\left[max\{p; \hat{Q}_p(X|Y=y) < x\} + min\{p; \hat{Q}_p(X|Y=y) > x\}\right]}{2} \times 100$$

where $\hat{Q}_p(X|Y=y)$ are the fitted conditional quantiles.

- **CONDITONAL CUMULATIVE DENSITY FUNCTION (CDF)-BASED SGP**

The SGP based on this model is expressed in symbols as follows:

$$f(X|Y=y) = F_{X|Y=y}(X|Y=y) = \int_{-\infty}^{x} p_{X|Y}(u|Y)du$$

where $p_{X|Y}$ is the conditional probability density function of current year test scores given a prior year test score, and $F_{X|Y=y}$ represents the corresponding conditional cumulative density function.

- **MULTIDIMENSIONAL ITEM RESPONSE THEORY (MIRT)-BASED SGP**

The SGP in this model is defined within multidimensional item response theory framework.

$$t(\theta_c|\theta_p) = F_{\theta_c|\theta_p}(\theta_c|\theta_p) = \int_{-\infty}^{\theta_c} p_{\theta_c|\theta_p}(u|\theta_p)du$$

where $p_{\theta_c|\theta_p}$ is the conditional probability density function of current abilities given a prior year's ability level, and $F_{\theta_c|\theta_p}$ represents the corresponding conditional cumulative density function.

METHODS

- **SETTING UP LONGITUDINAL DATA**

```
CALL RANDGEN(A_P, "LOGNORMAL", 0, 0.5);CALL RANDGEN(A_C, "LOGNORMAL", 0, 0.5);
CALL RANDGEN(B_P, "NORMAL", -0.2, 1);CALL RANDGEN(B_C, "NORMAL", 0, 1);
CALL RANDGEN(C_P, "BETA", 6, 16);CALL RANDGEN(C_C, "BETA", 6, 16);
THETA_MEAN = {-0.2, 0}; COV = {1 0.85, 0.85 1};
```

- **QR-BASED SGP**

```
PROC QUANTREG
      DATA = RSDATA CI = NONE ALGORITHM = SMOOTH
      PLOTS(MAXPOINTS=20000) = FITPLOT(NOLIMITS);
      EFFECT SP = SPLINE( RS_P / KNOTMETHOD = LIST
                               (13 16 19 22));
      MODEL RS_C = SP / QUANTILE = 0.01 TO 0.99 BY 0.01;
      OUTPUT OUT = MYRESULT PRED=P;
RUN;
```

- **CDF-BASED SGP**

```
PROC UNIVARIATE DATA = MYOUT NOPRINT;
      VAR RS_P RS_C;
      CLASS RS_P;
      CDFPLOT RS_C / OVERLAY;
RUN;
```

- **MIRT-BASED SGP**

```
PROC IRT DATA = MYRESULT OUT = IRT_OUT2 PLOTS = ICC SCOREMETHOD = EAP;
      VAR I_C1 - I_C35;
      MODEL I_C1 - I_C35/RESFUNC = THREEP;
RUN;
```

- **COMPARISON**

```
DATA SGP_COMP4;
      RETAIN ID QR_SGP CDF_SGP MIRT_SGP;
      SET SGP_COMP3;
      DROP RS_P RS_C THETA_P THETA_C; /* ID / QR_SGP / CDF_SGP / MIRT_SGP */
RUN;
```

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RESULTS

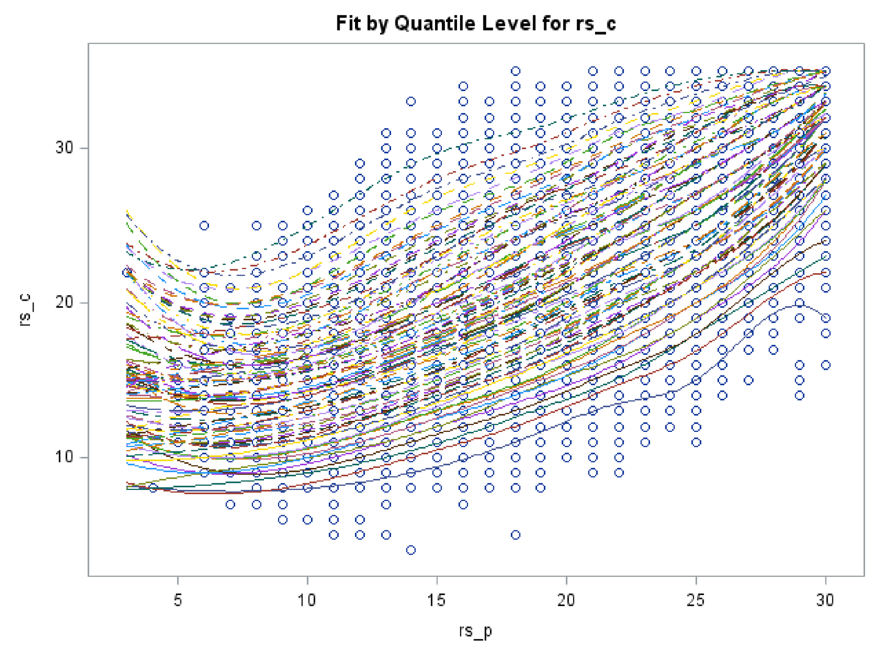


Figure1. Scatter plot with quantile regression lines

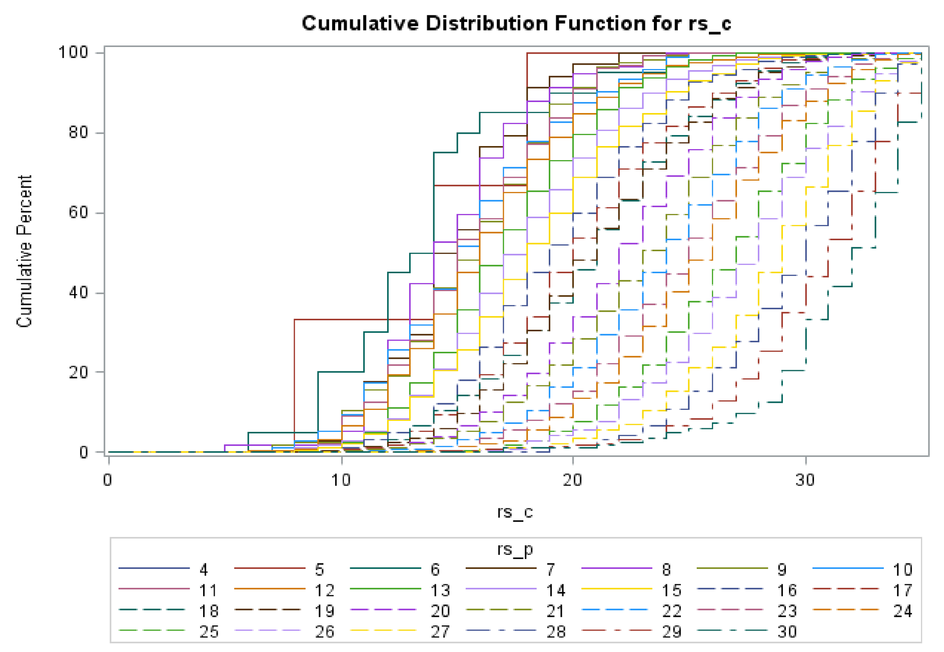


Figure2. Conditional Cumulative Distribution Function of x given y

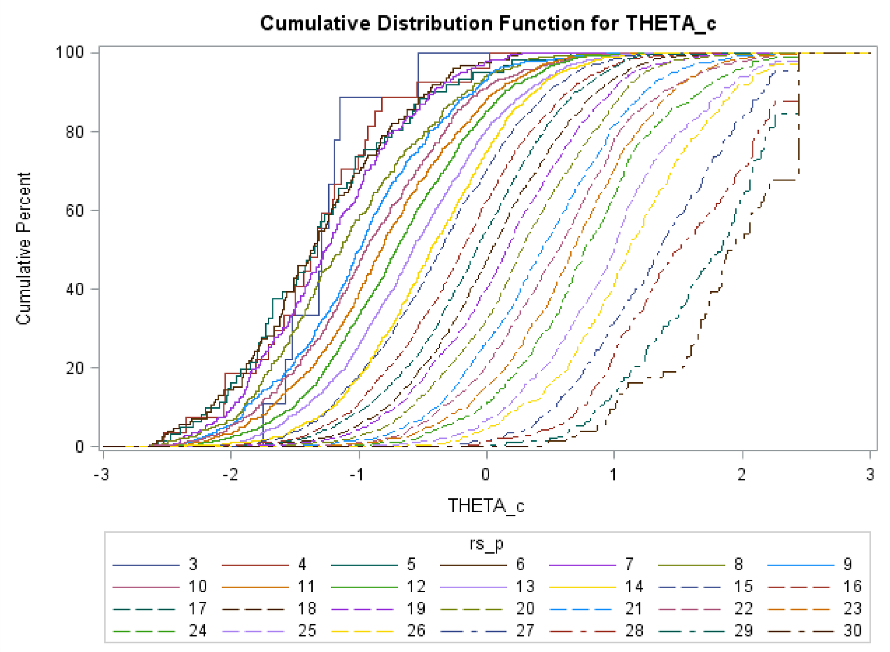


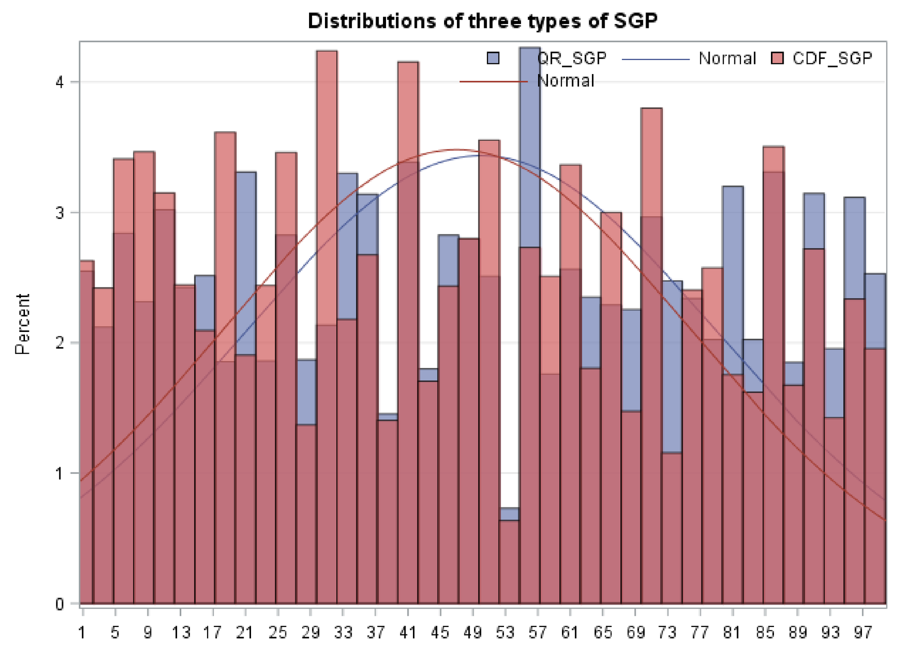
Figure3. Conditional Cumulative Distribution Function of θ_c given y

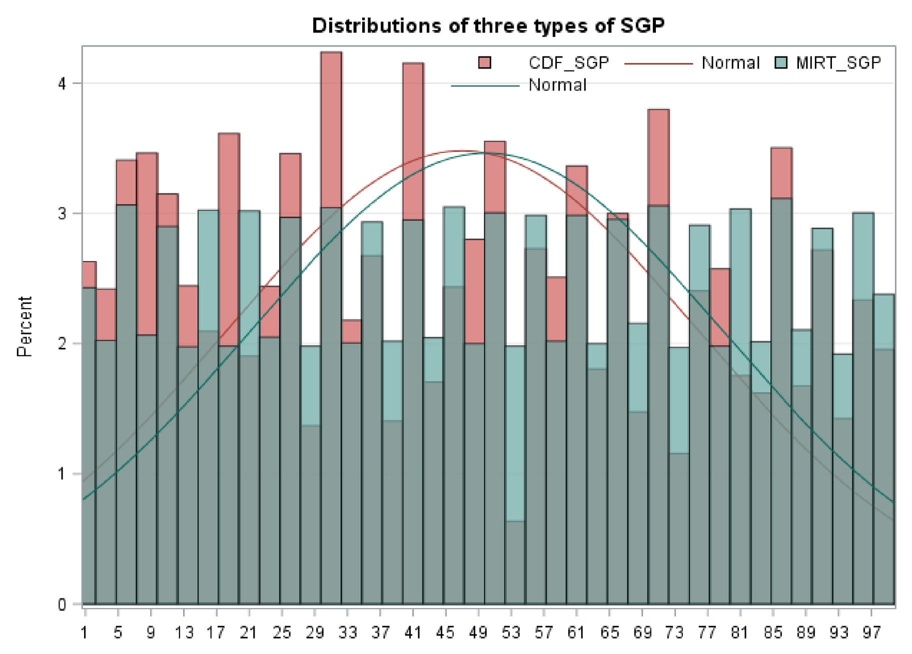
Obs	ID	QR_SGP	CDF_SGP	MIRT_SGP
1	1	48	44	39
2	2	49	49	43
3	3	31	29	17
4	4	35	30	36
5	5	25	19	31
6	6	62	57	70
7	7	24	23	12
8	8	48	44	49
9	9	98	97	97
10	10	84	80	84

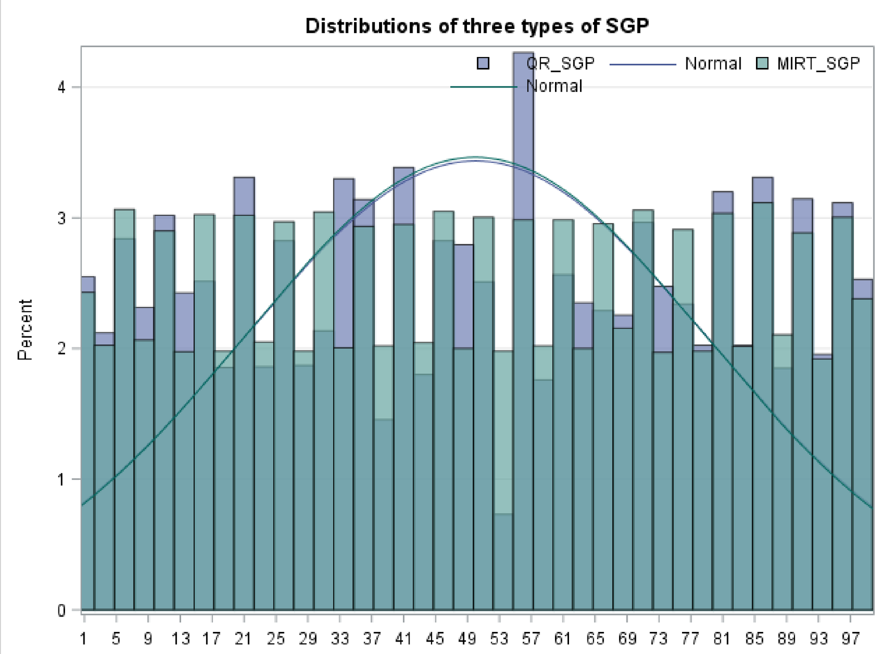
Table 1. Estimations of QR-, CDF-, and MIRT-based SGP of the first 10 examinees

- **Figure 1** shows the predicted 99 quantile regression lines with observations. This approach applied non-parametric technique (spline basis function) for fitting dataset.
- **Figure 2** shows the stair shape of conditional CDF given a number-correct score of the prior year's test.
- **Figure 3** shows smoother conditional CDF than **Figure 2**. However, due to the lack of the sample size at the extreme range of scores, the areas are similar to those in **Figure 2**.

RESULTS







- CDF-based approach tends to have smaller values of SGP than QR-based and MIRT-based approaches.
- MIRT-based approach tends to have more various SGP values, which means that the estimated SGPs are spread out within the possible range of SGP (i.e, from 1 to 99).
- In terms of normal fit, QR-based SGP ≈ MIRT-based SGP

CONCLUSIONS

- QR-based approach have larger bias at the scores lower than 5 points because of lack of sample sizes.
- CDF-based approach spent the shortest time to estimate all individuals' SGP. However, due to the discreteness of variables, the SGPs were estimated as the limit numbers among all possible SGP values ranged from 1 to 99.
- MIRT-based approach required the longest time to run the program code (more than 9 mins.), and some people could not obtain ability estimates due to the issue of convergence in algorithm.
- As a limitation of this study, a replication study should be conducted for establishing general patterns among the approaches considered.

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