

Ovarian Cancer Histotypes: Report of Statistical Findings

Derek Chiu

2020-10-09

Contents

Preface	4
1 Introduction	5
2 Methods	6
2.1 Data Processing	6
2.2 Classification	10
3 Validation	11
3.1 Concordance	11
3.2 Full Data Distributions	15
3.3 Training Set Distributions	15
3.4 Normalization	19
3.5 Common Sample Distributions	26
4 Results	28
4.1 CS1	28
4.2 CS2	31

List of Tables

3.1	All CodeSet Histotype Groups	15
3.2	All CodeSet Histotypes	16
3.3	Common Summary ID CodeSet Histotypes	16
3.4	All CodeSet Major Histotypes	16
3.5	CS1 Histotypes	17
3.6	CS2 Histotypes	17
3.7	CS3 Histotypes	18
3.8	CS1 Training Set Histotypes	18
3.9	CS2 Training Set Histotypes	18
3.10	All Common Samples Histotype Distribution	26
3.11	Distinct Common Samples Histotype Distribution	27

List of Figures

3.1	Gene Expression CS2 No Normalization vs. CS3	12
3.2	Gene Expression CS2 Pools Normalization vs. CS3	13
3.3	Gene Expression CS2 Reference Normalization vs. CS3	14
3.4	Concordance Histograms	15
3.5	Random3 Non-Normalized Concordance Measure Distributions	20
3.6	Random3 Normalized Concordance Measure Distributions	21
3.7	Random2 Non-Normalized Concordance Measure Distributions	22
3.8	Random2 Normalized Concordance Measure Distributions	23
3.9	Random1 Non-Normalized Concordance Measure Distributions	24
3.10	Random1 Normalized Concordance Measure Distributions	25
3.11	Pools Normalized Concordance Measure Distributions	26
4.1	CS1 Accuracy	28
4.2	CS1 F1-Score	29
4.3	CS1 Class-Specific F1-Score	30
4.4	CS2 Accuracy	31
4.5	CS2 F1-Score	32
4.6	CS2 Class-Specific F1-Score	33

Preface

This report of statistical findings describes the classification of ovarian cancer histotypes using data from NanoString CodeSets.

Marina Pavanello conducted the initial exploratory data analysis, Cathy Tang implemented class imbalance techniques, Derek Chiu conducted the normalization and statistical analysis, and Aline Talhouk lead the project.

1. Introduction

Ovarian cancer has five major histotypes: high-grade serous carcinoma (HGSC), low-grade serous carcinoma (LGSC), endometrioid carcinoma (ENOC), mucinous carcinoma (MUC), and clear cell carcinoma (CCOC). A common problem with classifying these histotypes is that there is a class imbalance issue. HGSC dominates the distribution, commonly accounting for 70% of cases in many patient cohorts, while the other four histotypes are spread over the rest of the cases.

In the NanoString CodeSets, we also run into a problem with trying to find suitable control pools to normalize the gene expression. For prospective NanoString runs, the pools can be specifically chosen, but for retrospective runs, we have to utilize a combination of common samples and common genes as references for normalization.

The supervised learning is performed under a consensus framework: we consider various classification algorithms and use evaluation metrics to help make decisions of which methods to carry forward for downstream analysis.

2. Methods

2.1 Data Processing

Normalizing CS2 to CS3 can easily follow the [PrOType](#) method for HGSC subtypes because both CodeSets have pool samples. A different technique is implemented when normalizing CS1 to CS3 where we use common samples and genes as reference sets.

2.1.1 Raw Data

There are 3 NanoString CodeSets:

- CS1: OvCa2103_C953
 - Samples = 412
 - Genes = 275
- CS2: PrOTYPE2_v2_C1645
 - Samples = 1223
 - Genes = 384
- CS3: OTTA2014_C2822
 - Samples = 5424
 - Genes = 532

These datasets contain raw counts extracted straight from NanoString RCC files.

2.1.2 Housekeeping Genes

The first normalization step is to normalize all endogenous genes to housekeeping genes (POLR1B, SDHA, PGK1, ACTB, RPL19; reference genes expressed in all cells). We normalize by subtracting the average \log_2 housekeeping gene expression from the \log_2 endogenous gene expression. The updated CodeSet dimensions are now:

- CS1: OvCa2103_C953
 - Samples = 412
 - Genes = 256
- CS2: PrOTYPE2_v2_C1645
 - Samples = 1223
 - Genes = 365

- CS3: OTTA2014_C2822
 - Samples = 5424
 - Genes = 513

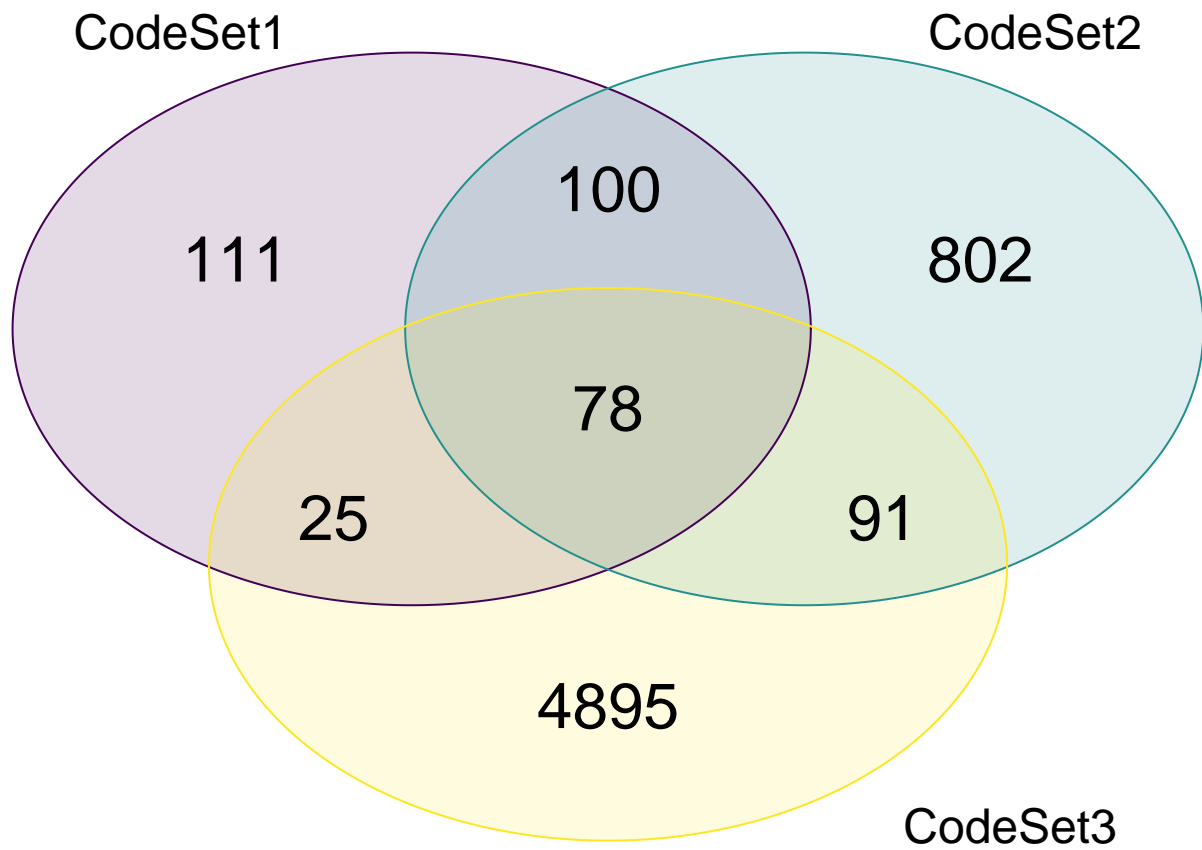
The number of genes are reduced by 19: 5 housekeeping, 8 negative, 6 positive (the latter 2 types are not used).

2.1.3 Common Samples and Genes

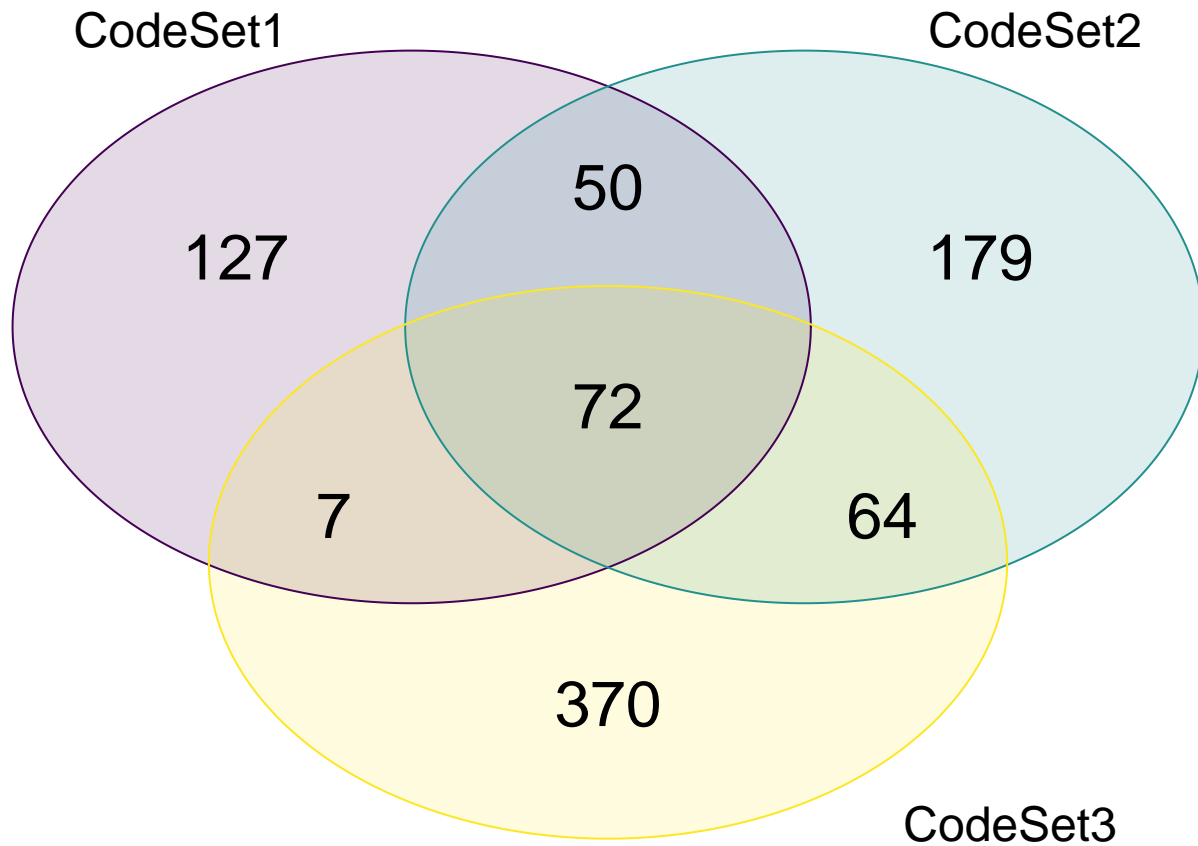
Since the reference pool samples only exist in CS2 and CS3, we need to find an alternative method to normalize all three CodeSets. One method is to select common samples and common genes that exist in all three. We found 72 common genes. Using the `summaryID` identifier, we also found 78 common summary IDs, translating to 320 samples. The number of samples that were matched to each CodeSet differed:

- CS1: OvCa2103_C953
 - Samples = 93
 - Genes = 72
- CS2: PrOTYPE2_v2_C1645
 - Samples = 87
 - Genes = 72
- CS3: OTTA2014_C2822
 - Samples = 140
 - Genes = 72

2.1.3.1 Overlap of common samples by summary ID



2.1.3.2 Overlap of common genes



*Excluding housekeeping genes and controls

2.1.4 CS1 Training Set Generation

We use the reference method to normalize CS1 to CS3.

- CS1 reference set: duplicate samples from CS1
 - Samples = 25
 - Genes = 72
- CS3 reference set: corresponding samples in CS3 also found in CS1 reference set
 - Samples = 20
 - Genes = 72
- CS1 validation set: remaining CS1 samples with reference set removed
 - Samples = 387
 - Genes = 72

The final CS1 training set has 304 samples on 72 genes after normalization and keeping only the major histotypes of interest.

2.1.5 CS2 Training Set Generation

We use the pool method to normalize CS2 to CS3 so we can be consistent with the PrOType normalization when there are available pools.

- CS2 pools:
 - Samples = 9 (Pool 1 = 3, Pool 2 = 3, Pool 3 = 3)
 - Genes = 365
- CS3 pools:
 - Samples = 22 (Pool 1 = 12, Pool 2 = 5, Pool 3 = 5)
 - Genes = 513
- CS2 validation set: CS2 samples with pools removed
 - Samples = 1214
 - Genes = 365

The final CS2 training set has 945 samples on 136 (common) genes after normalization and keeping only the major histotypes of interest.

2.2 Classification

We use 6 classification algorithms and 4 subsampling methods across 500 repetitions in the supervised learning framework for CS1 and CS2. The pipeline was run using many SGE batch jobs as a way of parallelization on a CentOS 5 server. Implementations of the techniques below were called from the [splendid](#) package.

- Classifiers:
 - Random Forest
 - Adaboost
 - XGBoost
 - LDA
 - SVM
 - K-Nearest Neighbours
- Subsampling:
 - None
 - Down-sampling
 - Up-sampling
 - SMOTE

3. Validation

3.1 Concordance

First we validate the CS2 normalization process by looking at the distribution of CS3 non-normalized samples with:

- CS2 non-normalized
- CS2 pools-normalized
- CS2 reference-normalized

CS2 Validation Set (n=69) vs. Corresponding CS3 Samples

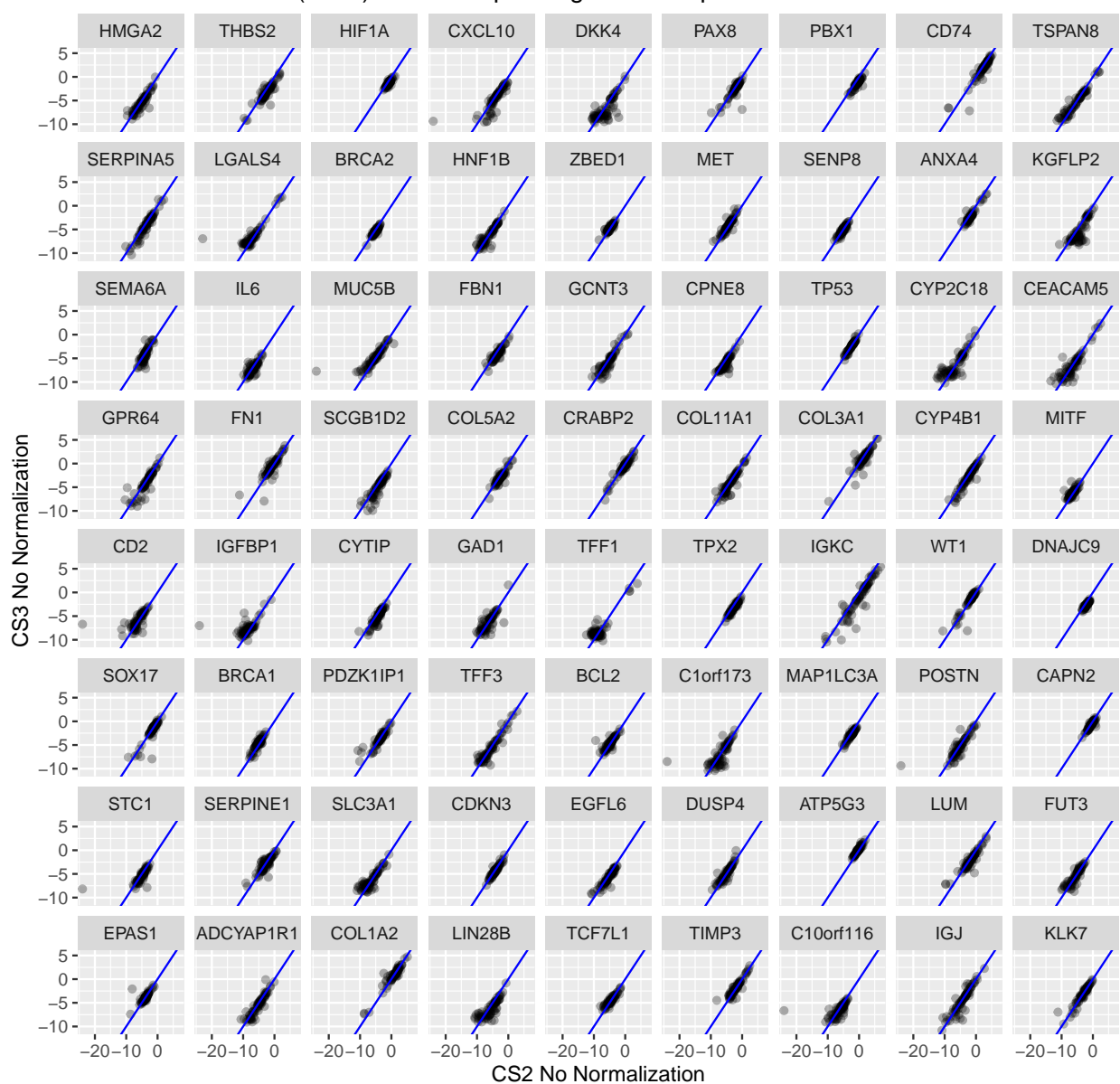


Figure 3.1: Gene Expression CS2 No Normalization vs. CS3

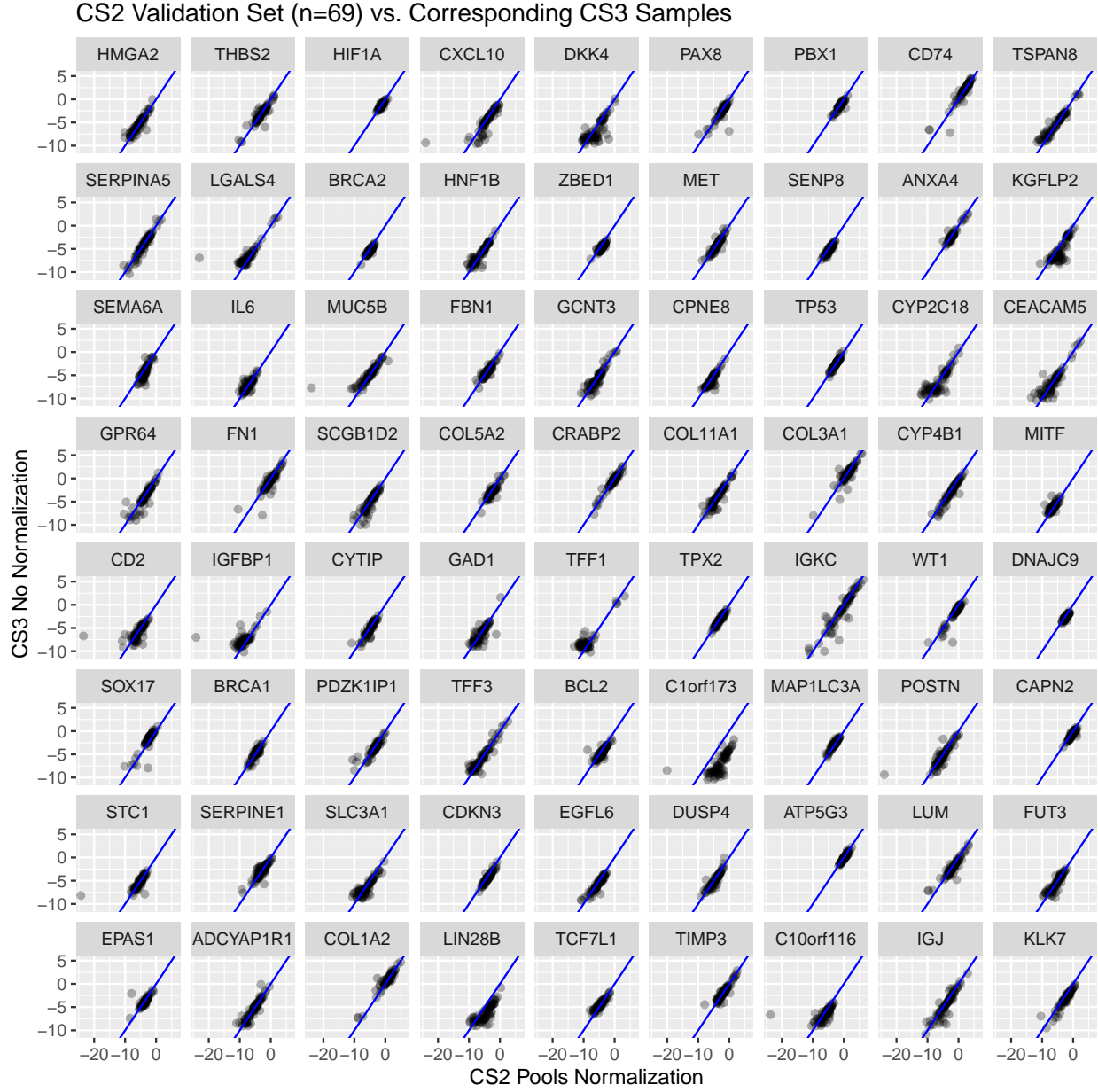


Figure 3.2: Gene Expression CS2 Pools Normalization vs. CS3

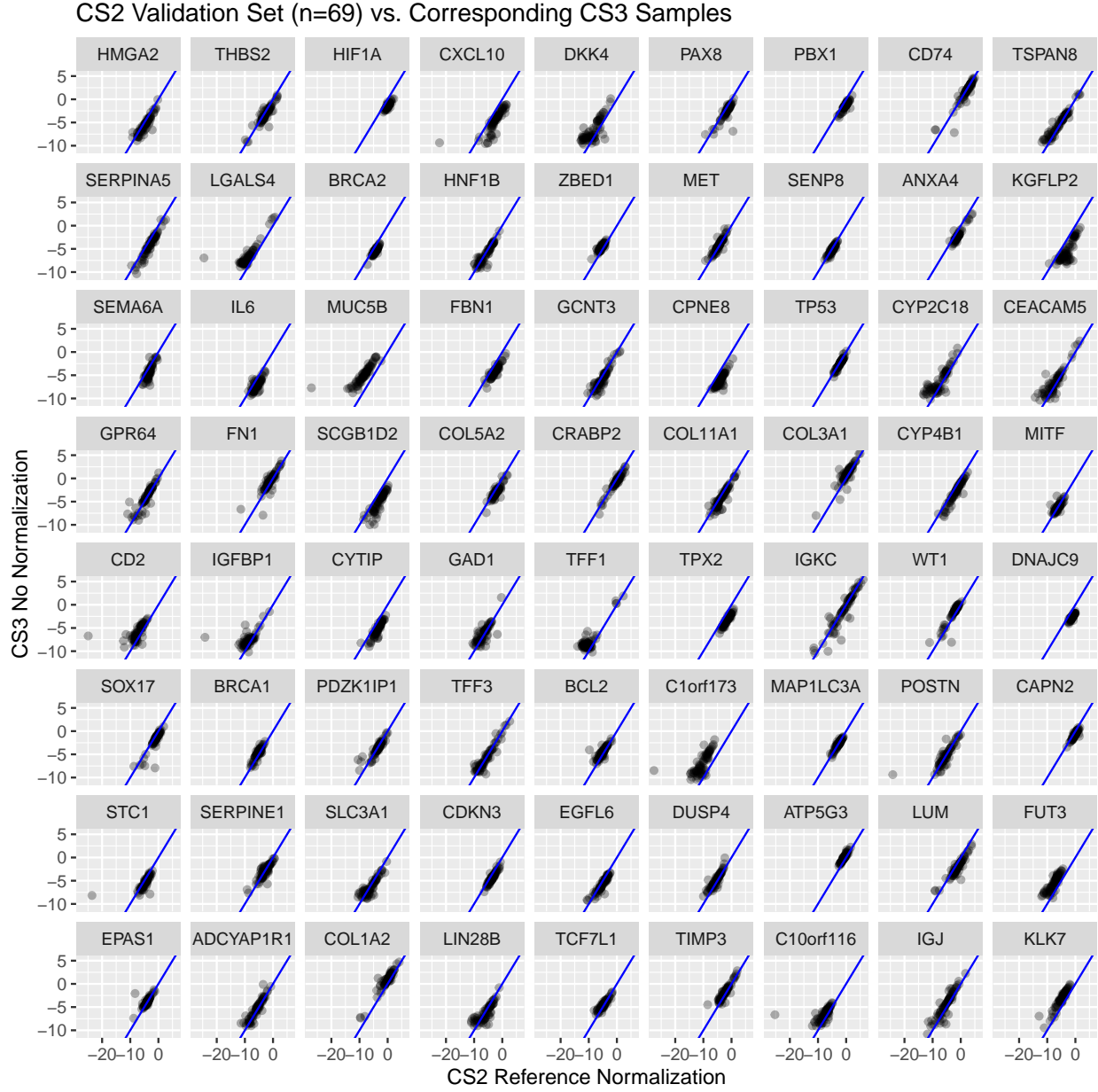


Figure 3.3: Gene Expression CS2 Reference Normalization vs. CS3

Table 3.1: All CodeSet Histotype Groups

hist_gr	CS1	CS2	CS3
HGSC	169	757	2453
non-HGSC	196	377	677

CS2 Datasets vs. CS3 Concordance Measure Distributions

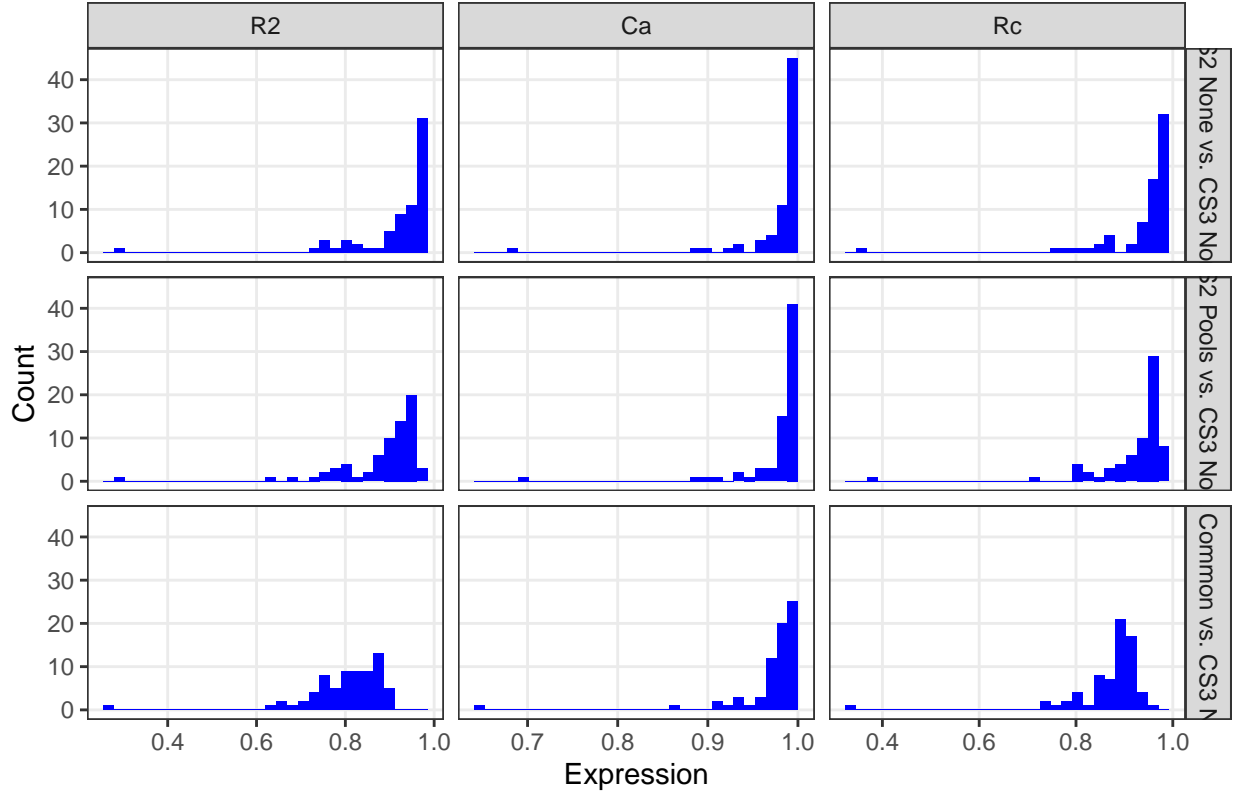


Figure 3.4: Concordance Histograms

3.2 Full Data Distributions

The histotype distributions on the full data are shown below.

3.3 Training Set Distributions

The training set distributions for CS1 and CS2 are shown below.

Table 3.2: All CodeSet Histotypes

revHist	CS1	CS2	CS3
CARCINOMA-NOS	0	61	23
Carcinoma, NOS	0	0	2
CCOC	57	68	182
CCOC-MCT	0	1	0
Cell-Line	17	48	13
CTRL	0	12	0
ENOC	61	30	272
ENOC-CCOC	0	7	0
ERROR	0	3	0
HGSC	169	757	2453
HGSC-MCT	0	1	0
LGSC	22	29	50
MBOT	0	20	3
MET-NOP	0	21	0
MIXED (ENOC/CCOC)	0	0	1
MIXED (ENOC/LGSC)	0	0	1
MIXED (HGSC/CCOC)	0	0	1
mixed cell	0	0	7
MMMT	0	0	30
MUC	20	61	77
Other (use when 6, 7, or 9 is not distinguished) or unknown if epithelial	0	0	1
Other/Exclude	0	0	8
SBOT	19	10	3
Serous	0	0	2
serous LMP	0	0	1
SQAMOUS	0	1	0
UNK	0	4	0

Table 3.3: Common Summary ID CodeSet Histotypes

revHist	CS1	CS2	CS3
CCOC	3	4	9
Cell-Line	4	5	5
ENOC	4	4	9
HGSC	68	64	98
LGSC	7	5	8
MUC	7	5	11

Table 3.4: All CodeSet Major Histotypes

revHist	CS1	CS2	CS3	CS1_percent	CS2_percent	CS3_percent
CCOC	57	68	182	17.3	7.2	6.0
ENOC	61	30	272	18.5	3.2	9.0
HGSC	169	757	2453	51.4	80.1	80.9
LGSC	22	29	50	6.7	3.1	1.6
MUC	20	61	77	6.1	6.5	2.5

Table 3.5: CS1 Histotypes

CodeSet	revHist	n
CS1	CCOC	57
CS1	Cell-Line	17
CS1	ENOC	61
CS1	HGSC	169
CS1	LGSC	22
CS1	MUC	20
CS1	SBOT	19

Table 3.6: CS2 Histotypes

CodeSet	revHist	n
CS2	CARCINOMA-NOS	61
CS2	CCOC	68
CS2	CCOC-MCT	1
CS2	Cell-Line	48
CS2	CTRL	12
CS2	ENOC	30
CS2	ENOC-CCOC	7
CS2	ERROR	3
CS2	HGSC	757
CS2	HGSC-MCT	1
CS2	LGSC	29
CS2	MBOT	20
CS2	MET-NOP	21
CS2	MUC	61
CS2	SBOT	10
CS2	SQAMOUS	1
CS2	UNK	4

Table 3.7: CS3 Histotypes

CodeSet	revHist	n
CS3	CARCINOMA-NOS	23
CS3	Carcinoma, NOS	2
CS3	CCOC	182
CS3	Cell-Line	13
CS3	ENOC	272
CS3	HGSC	2453
CS3	LGSC	50
CS3	MBOT	3
CS3	MIXED (ENOC/CCOC)	1
CS3	MIXED (ENOC/LGSC)	1
CS3	MIXED (HGSC/CCOC)	1
CS3	mixed cell	7
CS3	MMMT	30
CS3	MUC	77
CS3	Other (use when 6, 7, or 9 is not distinguished) or unknown if epithelial	1
CS3	Other/Exclude	8
CS3	SBOT	3
CS3	Serous	2
CS3	serous LMP	1

Table 3.8: CS1 Training Set Histotypes

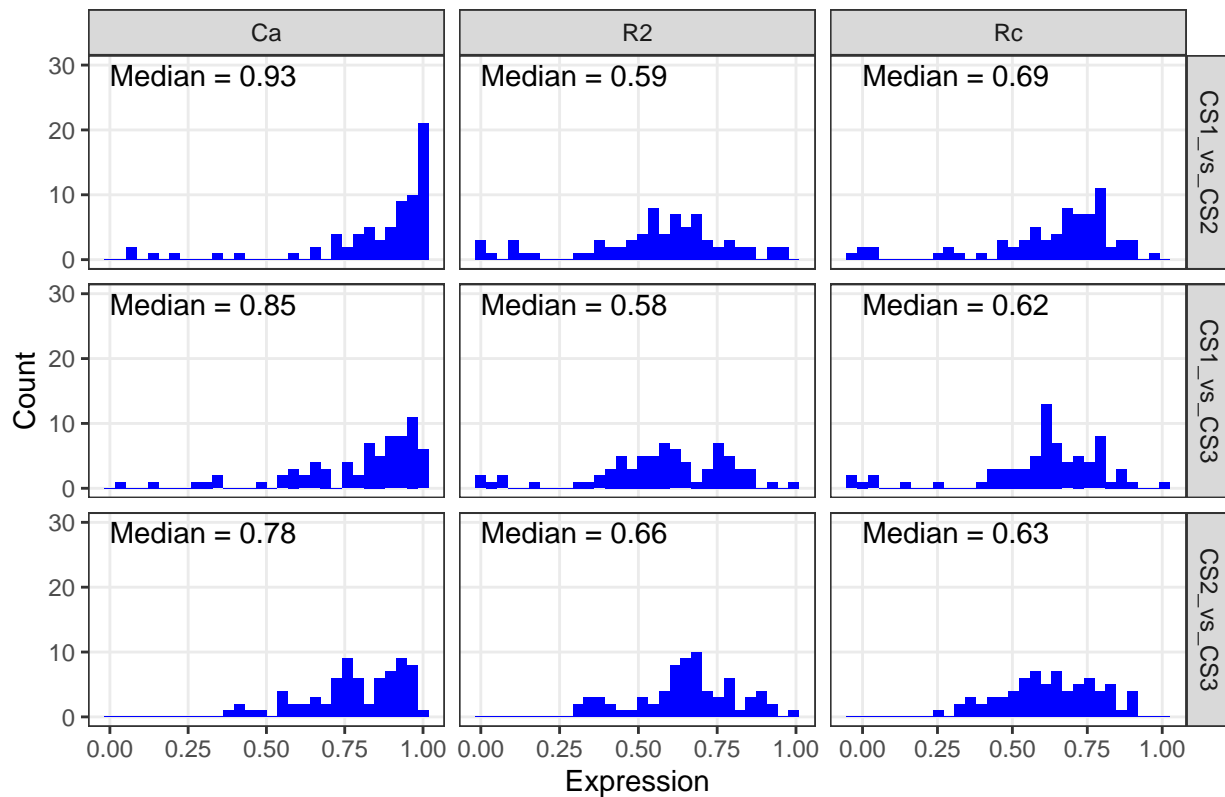
histotype	n
CCC	57
ENOCa	59
HGSC	156
LGSC	16
MUC	16

Table 3.9: CS2 Training Set Histotypes

histotype	n
CCOC	68
ENOC	30
HGSC	757
LGSC	29
MUC	61

3.4 Normalization

Raw Non-Normalized Concordance Measure Distributions



3.4.1 Reference Method

We employ a new normalization technique using randomly selected samples common to all three CodeSets with a uniform distribution of histotypes as the reference dataset. The number of randomly selected samples ranges from 1-3 per histotype. Hence, the reference dataset has either 5, 10, or 15 samples and we validate on the remaining. Note that ottaID duplicates are collapsed by mean averaging the gene expression.

Random3 Non-Normalized Concordance Measure Distributions

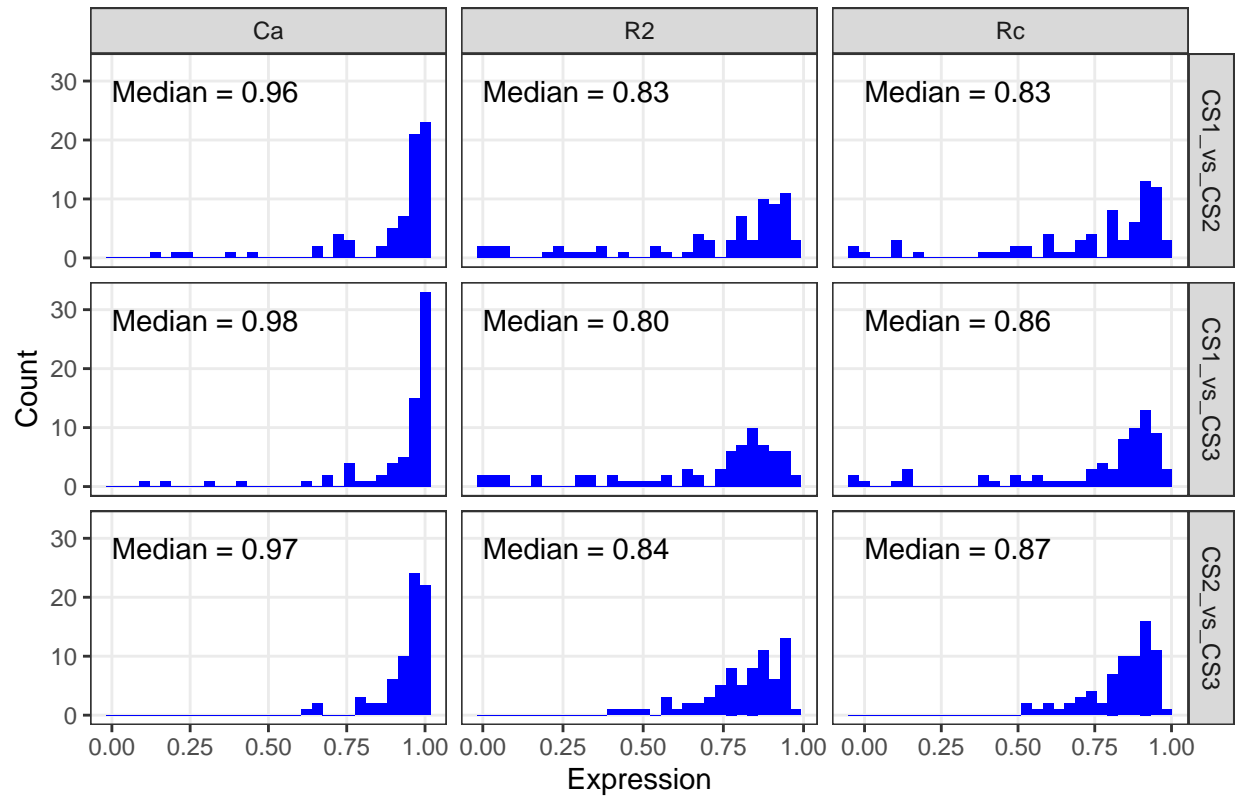


Figure 3.5: Random3 Non-Normalized Concordance Measure Distributions

Random3 Normalized Concordance Measure Distributions

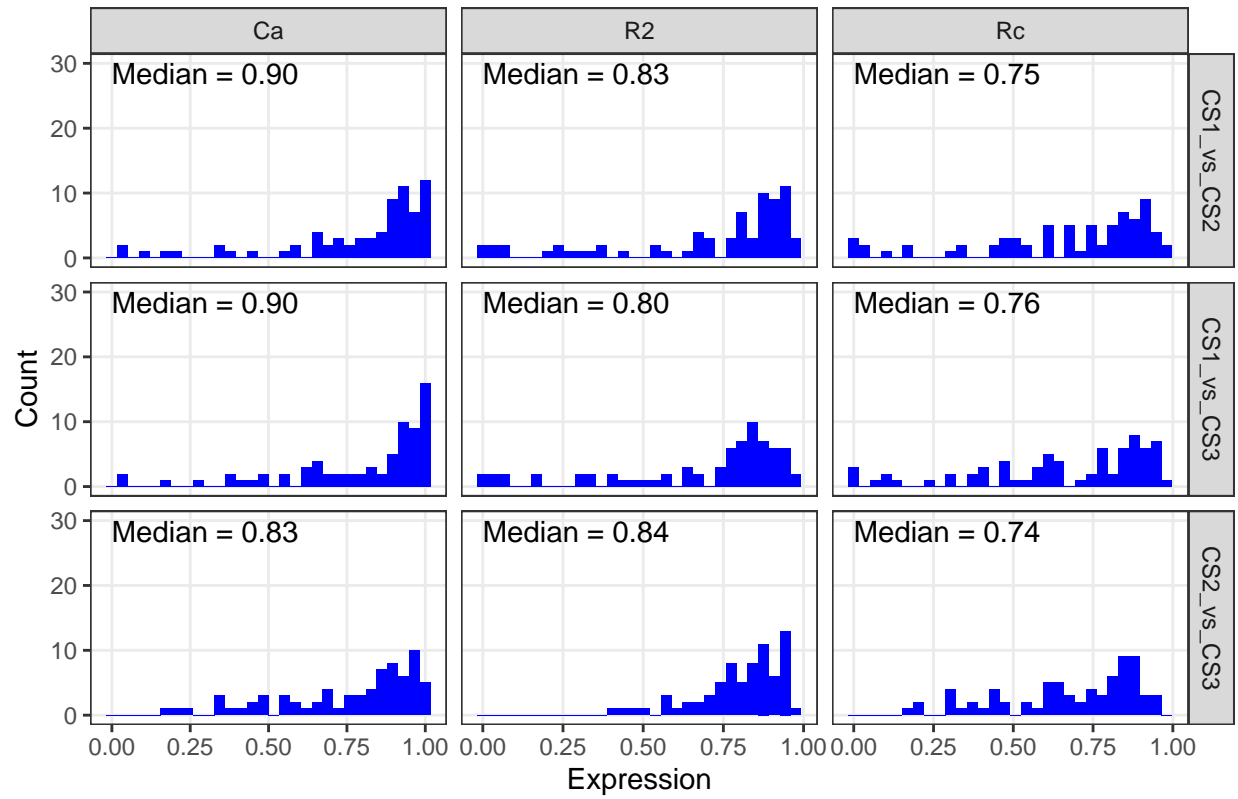


Figure 3.6: Random3 Normalized Concordance Measure Distributions

Random2 Non-Normalized Concordance Measure Distributions

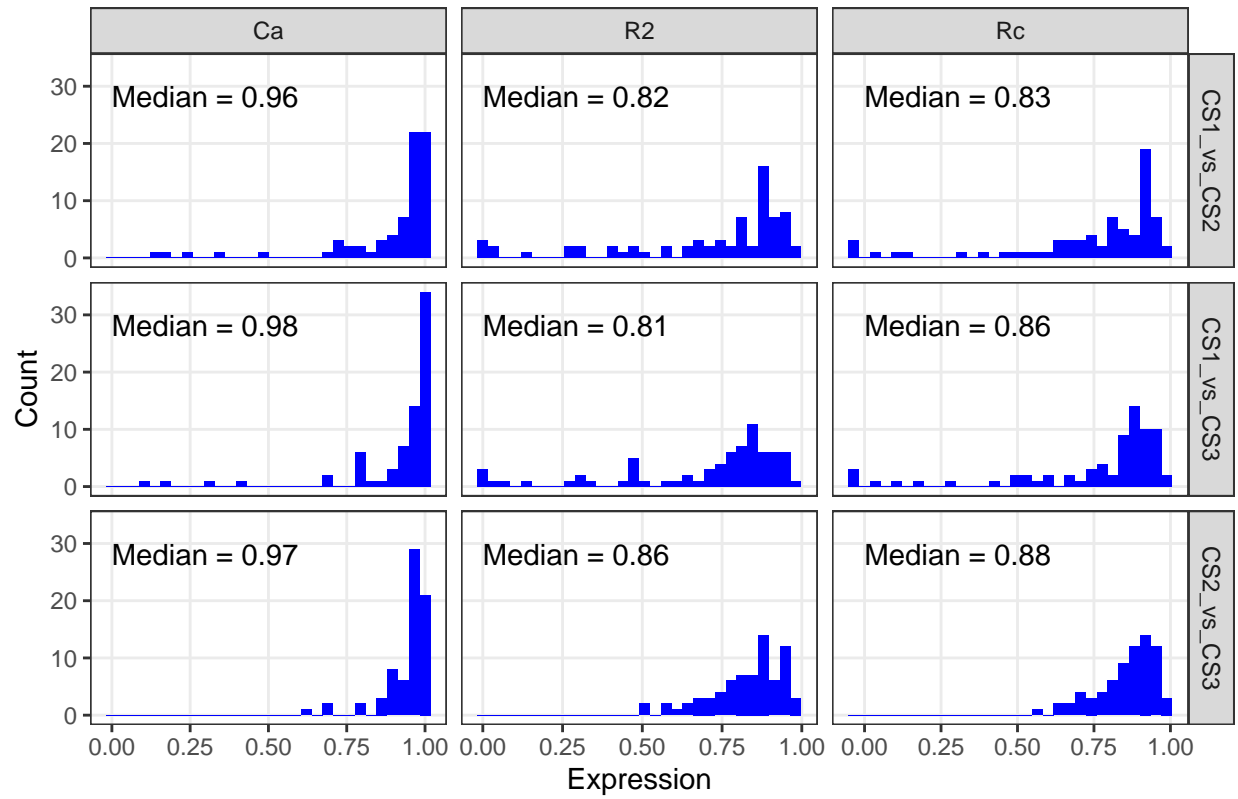


Figure 3.7: Random2 Non-Normalized Concordance Measure Distributions

Random2 Normalized Concordance Measure Distributions

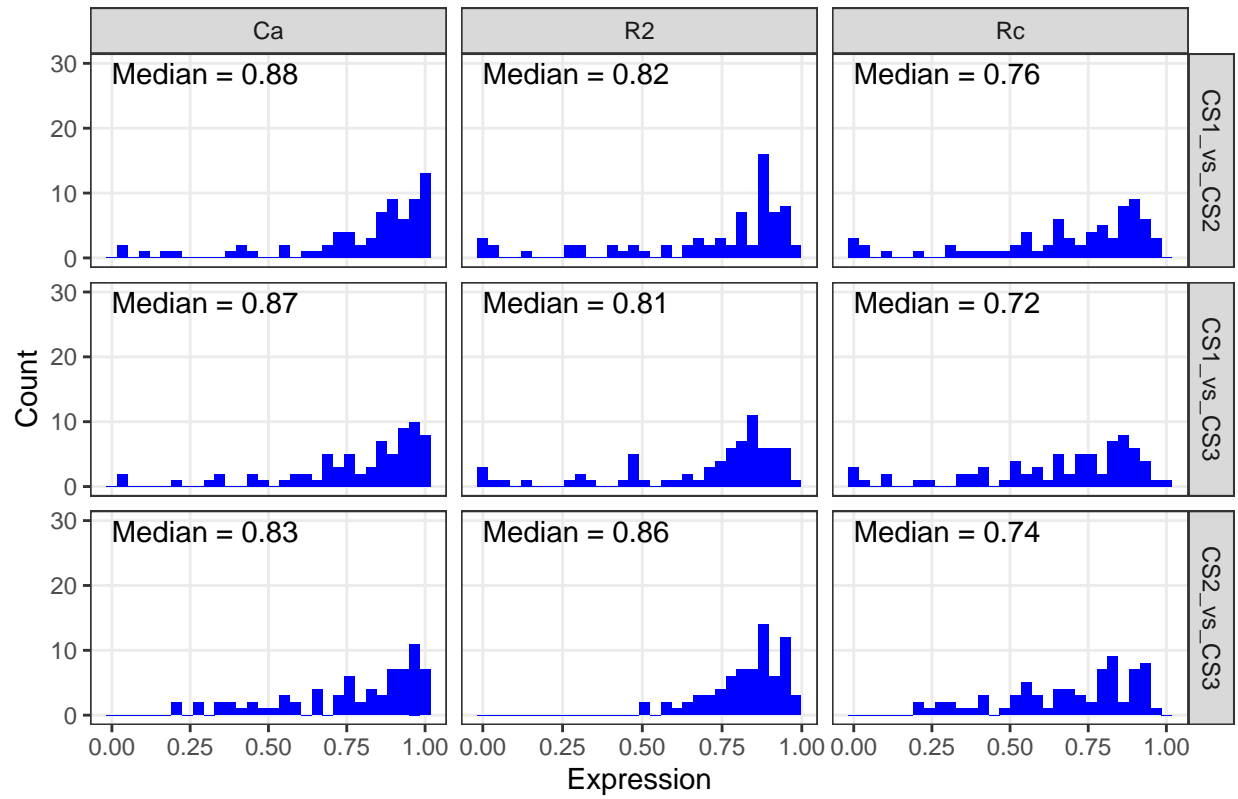


Figure 3.8: Random2 Normalized Concordance Measure Distributions

Random1 Non-Normalized Concordance Measure Distributions

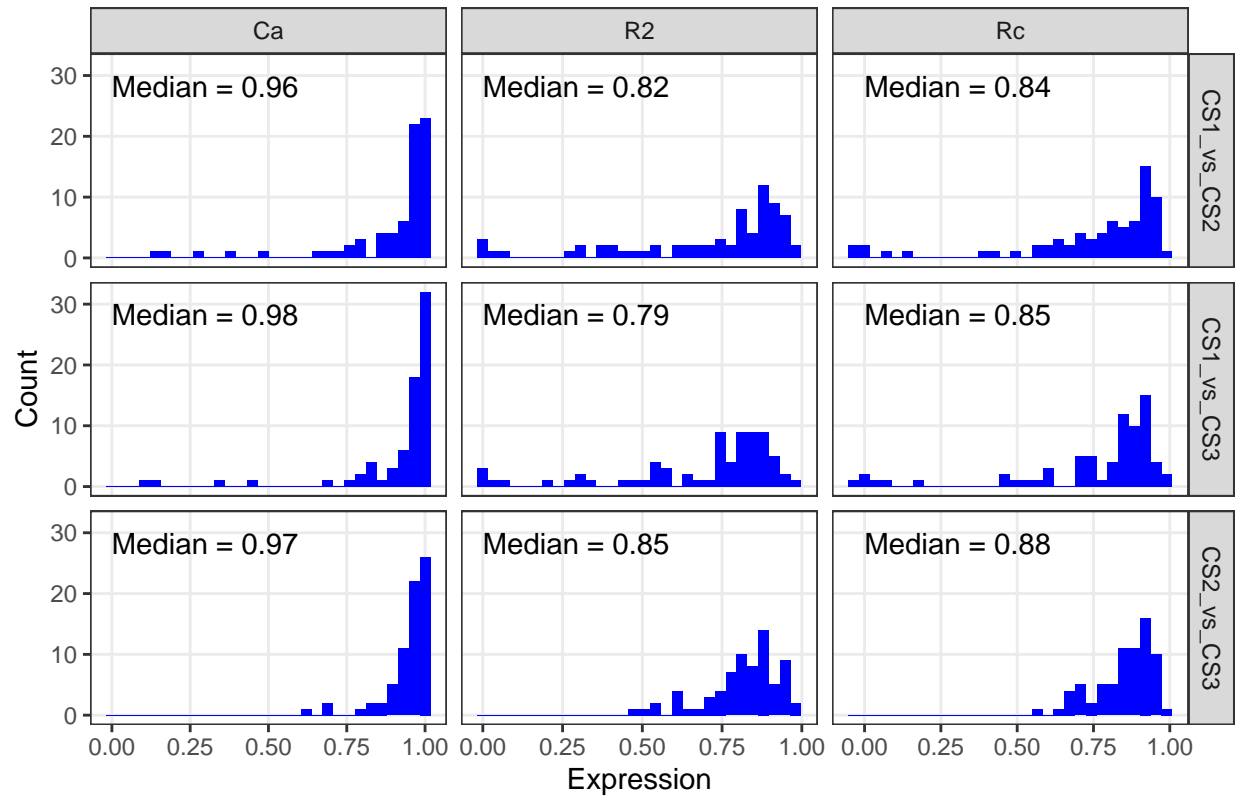


Figure 3.9: Random1 Non-Normalized Concordance Measure Distributions

Random1 Normalized Concordance Measure Distributions

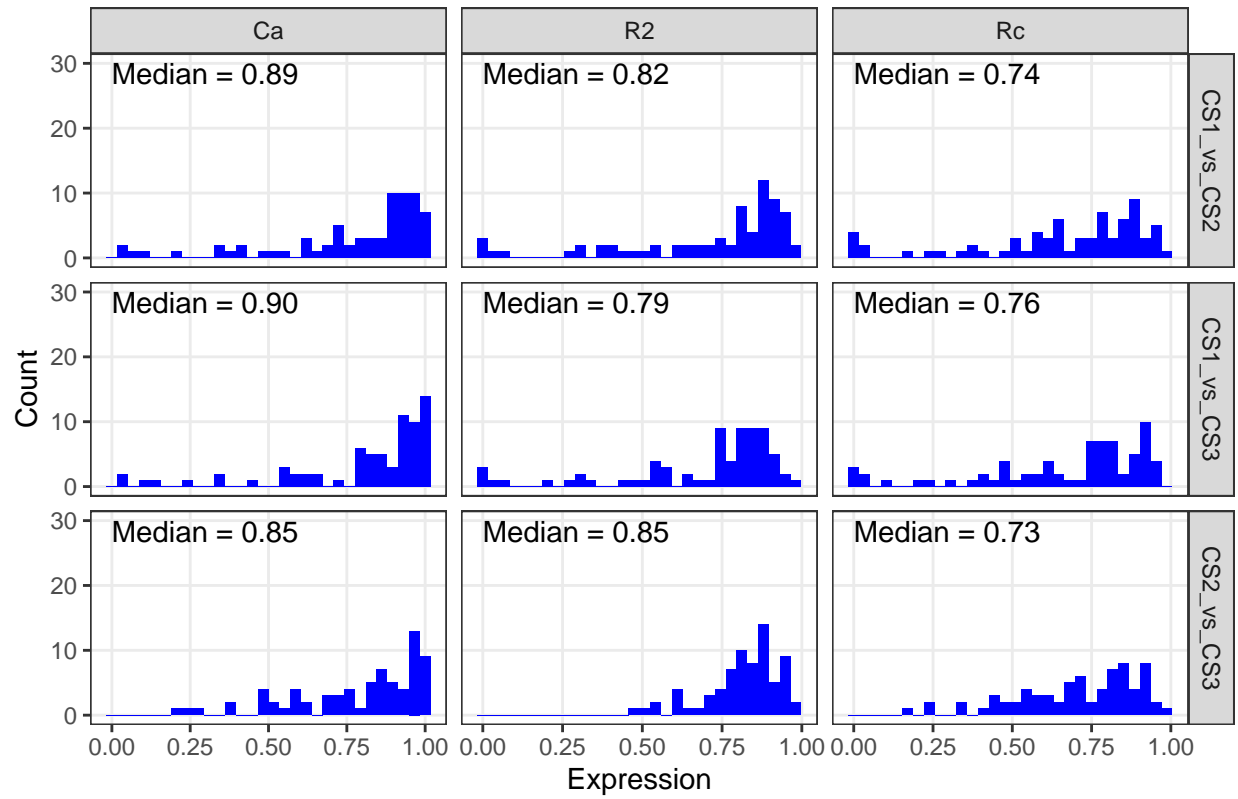


Figure 3.10: Random1 Normalized Concordance Measure Distributions

Table 3.10: All Common Samples Histotype Distribution

revHist	CS1	CS2	CS3
CCOC	3	4	9
ENOC	4	4	9
HGSC	59	62	95
LGSC	7	5	8
MUC	7	5	11

3.4.2 Pool Method

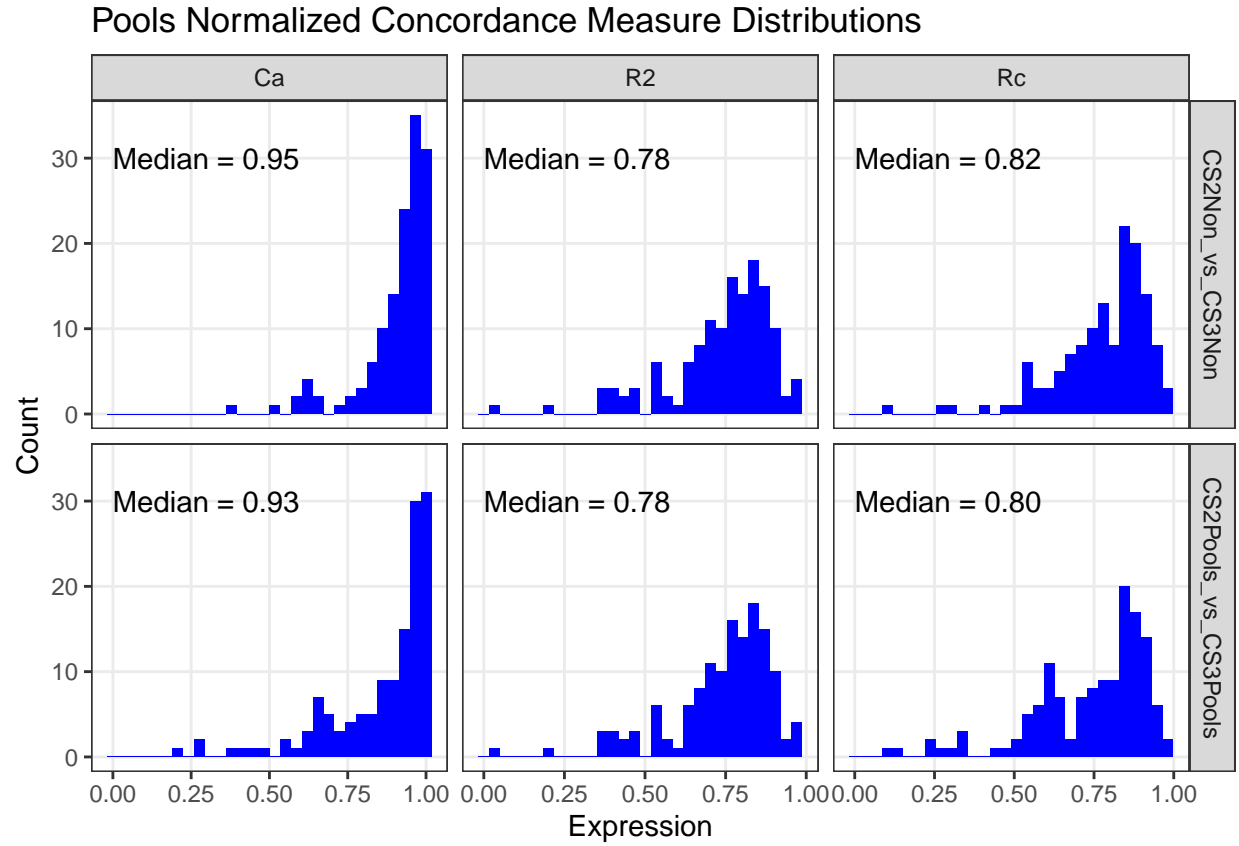


Figure 3.11: Pools Normalized Concordance Measure Distributions

3.5 Common Sample Distributions

Table 3.11: Distinct Common Samples Histotype Distribution

revHist	CS1	CS2	CS3
CCOC	3	3	3
ENOC	3	3	3
HGSC	57	57	57
LGSC	4	4	4
MUC	5	5	5

4. Results

Here we show internal validation summaries for both CS1 and CS2. The accuracy and F1-scores are the measures of interest. Algorithms are sorted by descending value. The point ranges show the median, 5th and 95th percentiles, coloured by subsampling methods.

4.1 CS1

4.1.1 Accuracy

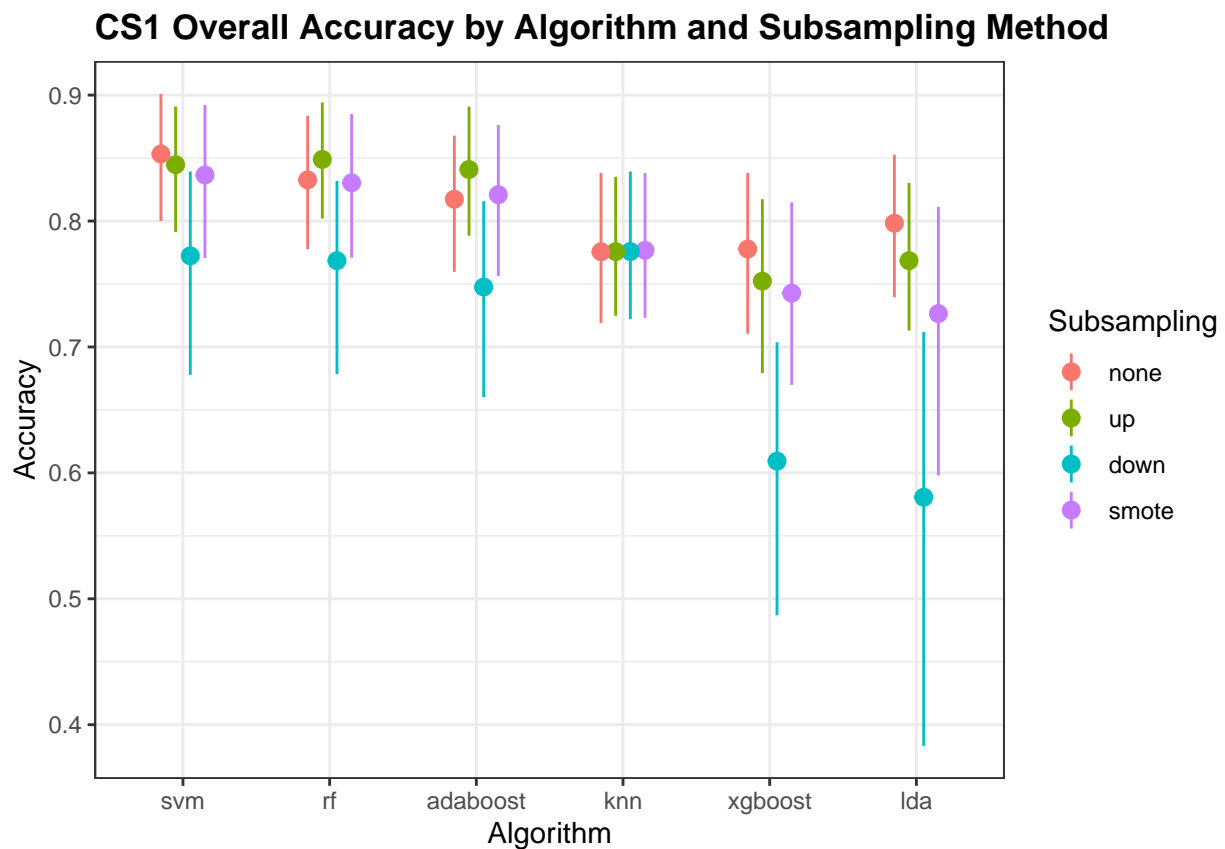


Figure 4.1: CS1 Accuracy

4.1.2 F1-Score

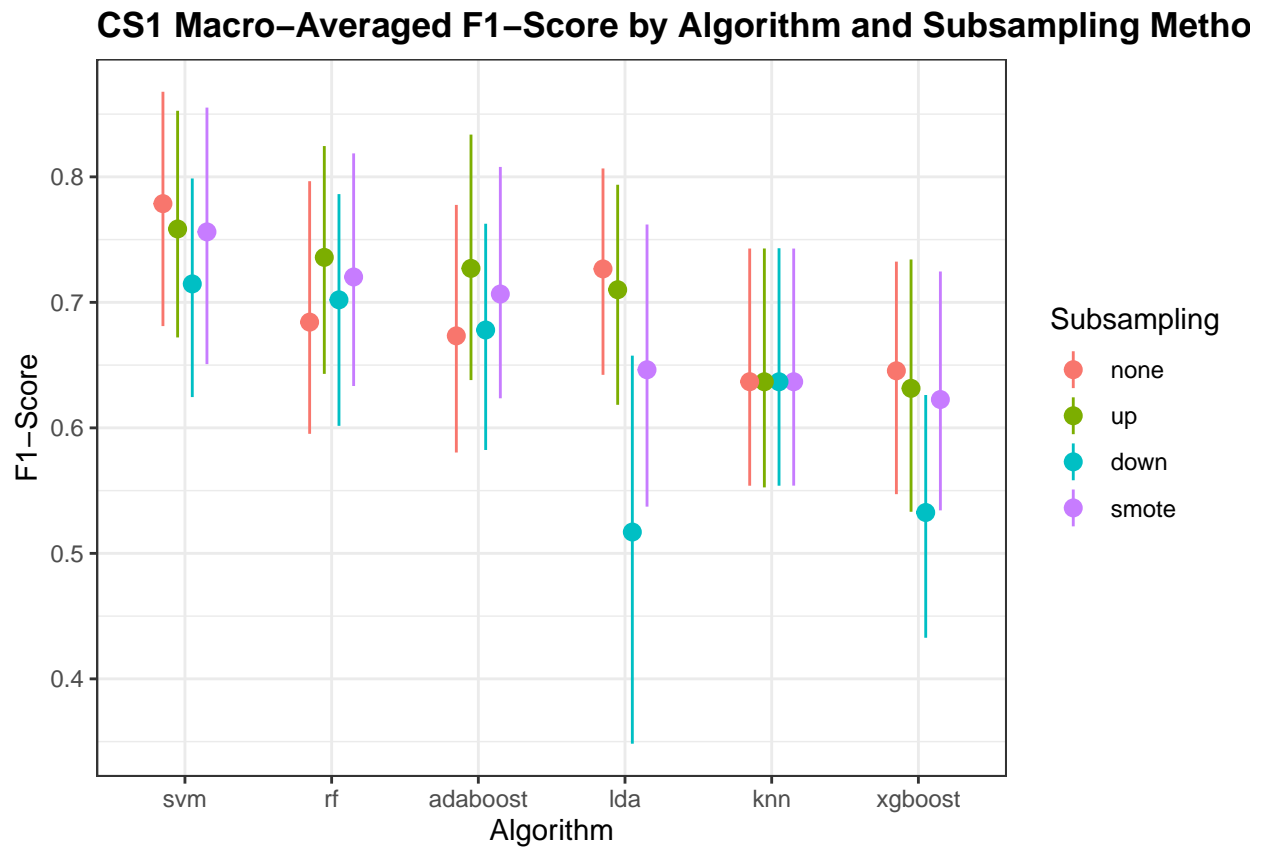


Figure 4.2: CS1 F1-Score

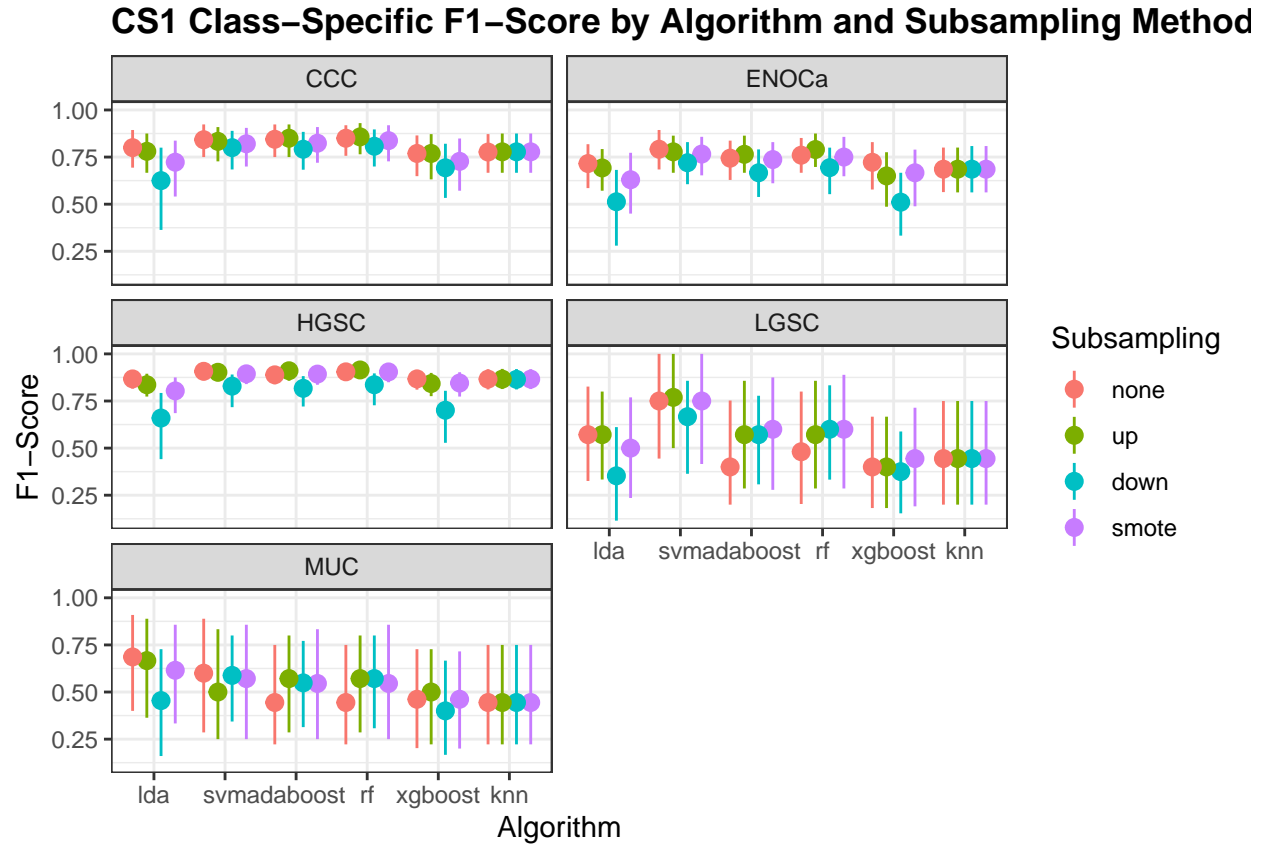


Figure 4.3: CS1 Class-Specific F1-Score

4.2 CS2

4.2.1 Accuracy

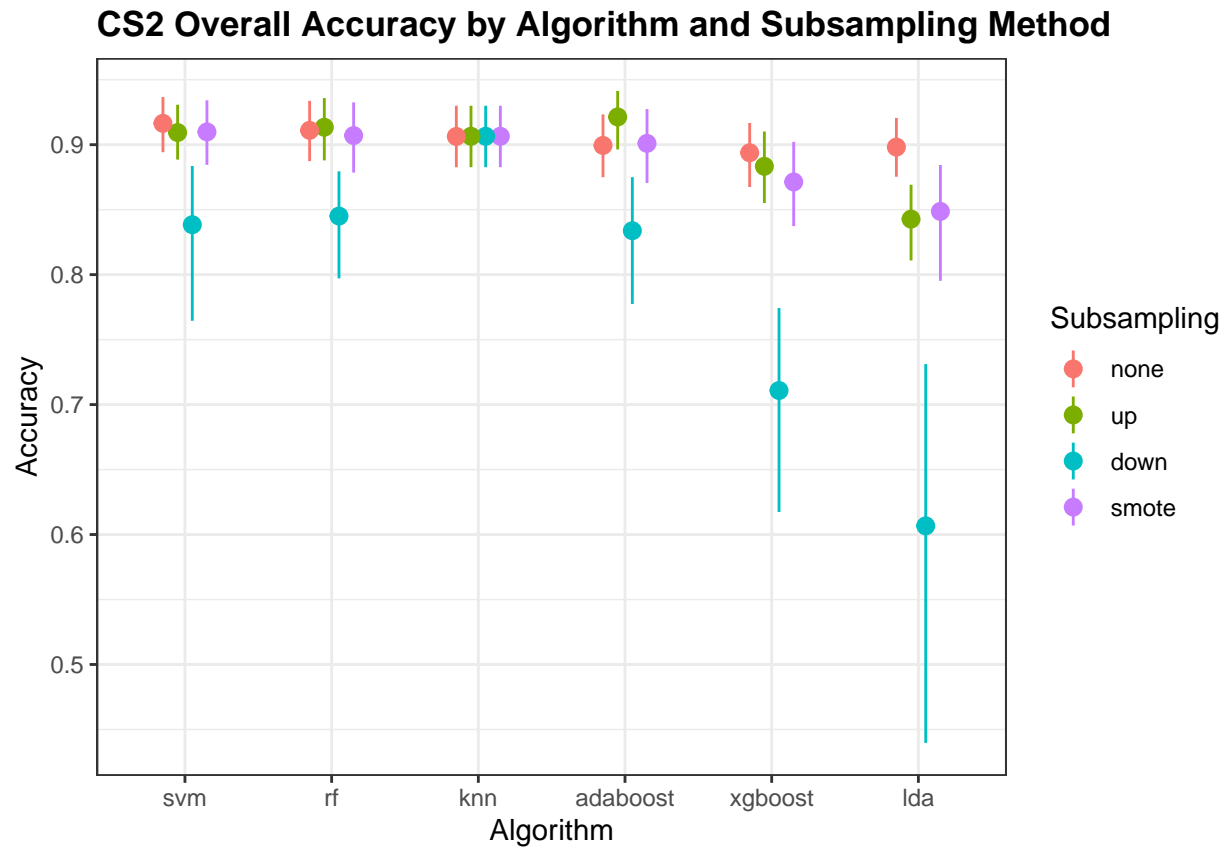


Figure 4.4: CS2 Accuracy

4.2.2 F1-Score

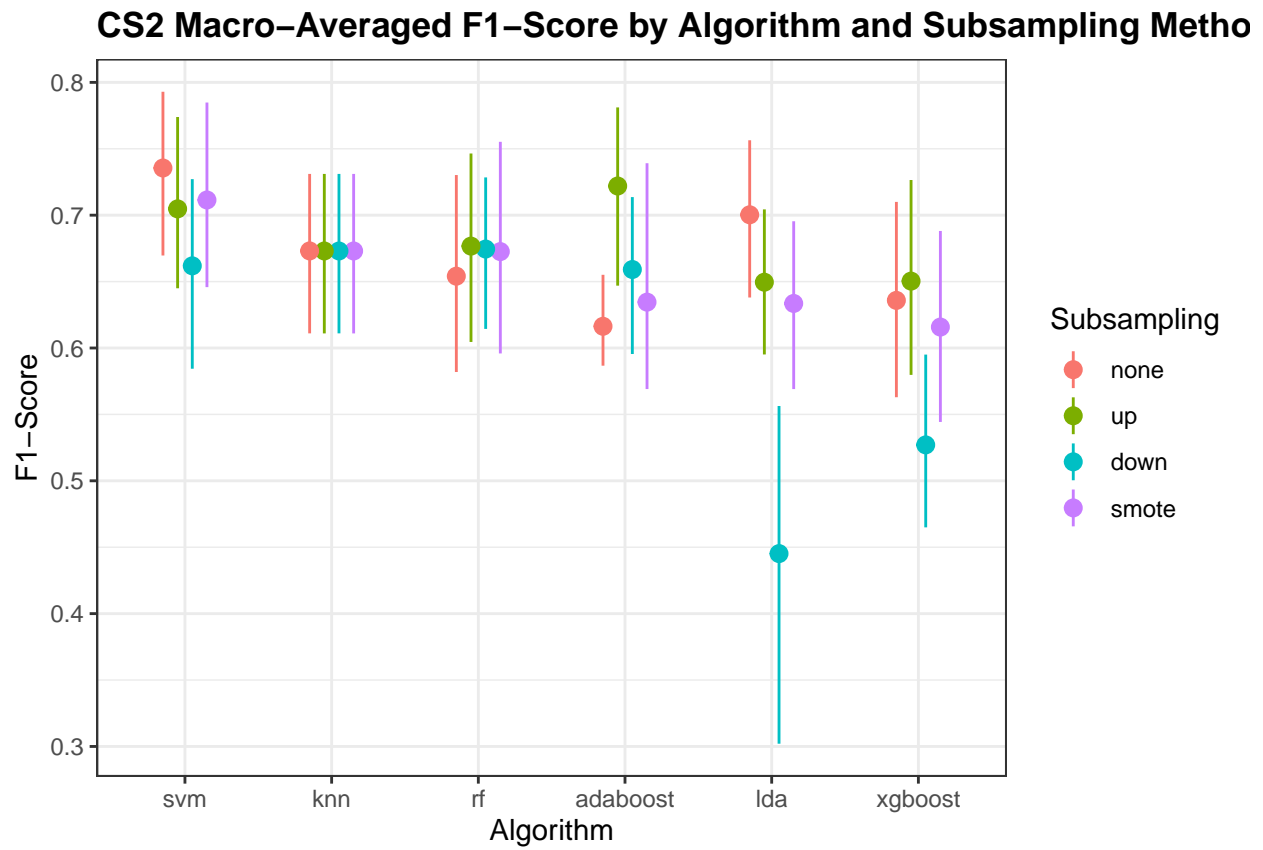


Figure 4.5: CS2 F1-Score

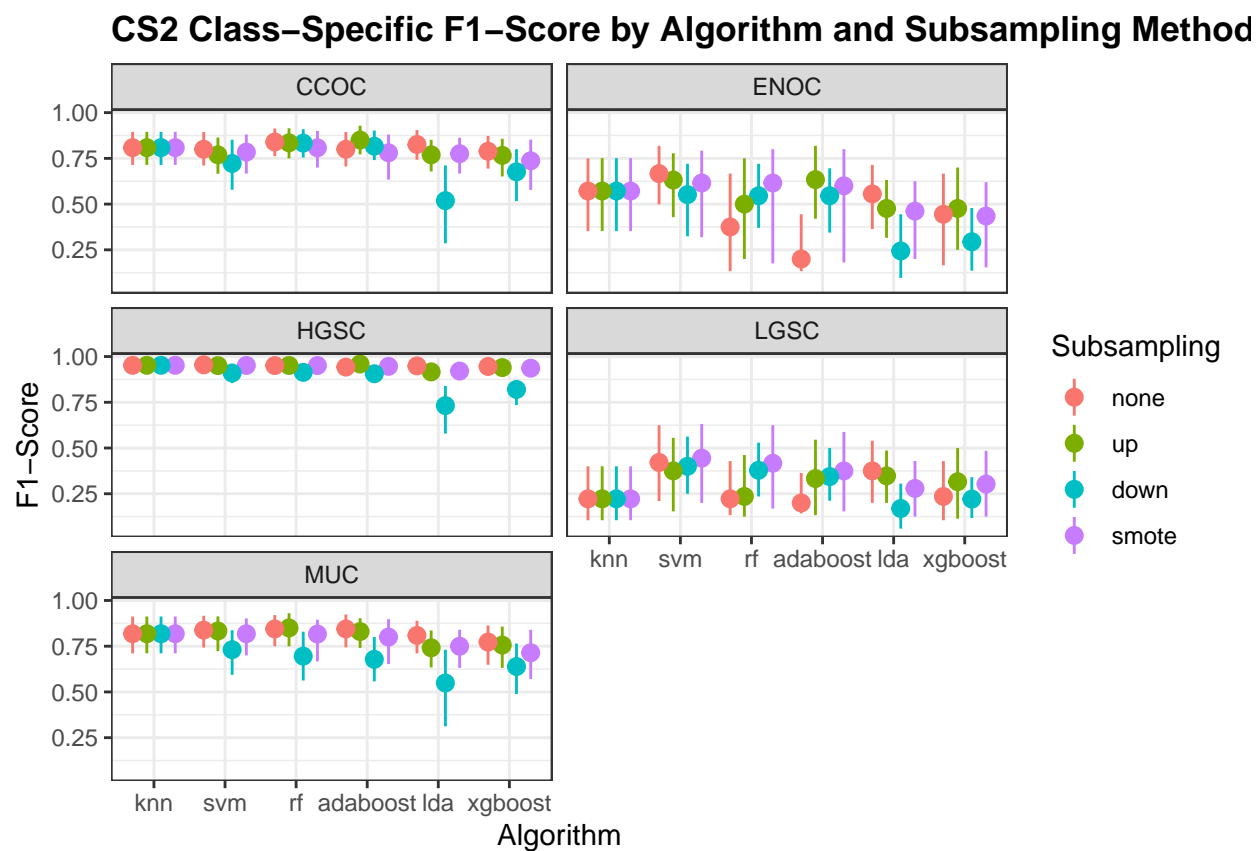


Figure 4.6: CS2 Class-Specific F1-Score