

Part 1

Students: ['i1', 'i2', 'i3', 'i4', 'i5', 'i6', 'i7', 'i8', 'i9', 'i10', 'i11', 'i12', 'i13', 'i14', 'i15', 'i16', 'i17', 'i18']

Schools: ['s1', 's2', 's3']

Capacity: {'s1': 6, 's2': 6, 's3': 6}

Example student preferences (first 5):

i1: ['s1', 's2', 's3']

i2: ['s1', 's2', 's3']

i3: ['s3', 's2', 's1']

i4: ['s1', 's3', 's2']

i5: ['s2', 's1', 's3']

Example school priorities (first 2 schools, top 8):

s1: ['i2', 'i17', 'i4', 'i12', 'i10', 'i7', 'i8', 'i3'] ...

s2: ['i10', 'i17', 'i16', 'i13', 'i7', 'i14', 'i4', 'i5'] ...

I=18, S=3, q=6

I construct a school choice market with 18 students and 3 schools, each school having a capacity of 6 seats. Thus, total capacity equals total demand (18). It ensures that a full matching is feasible (no shortage appear).

For each student, we generate a strict random preference ordering over the three schools. Similarly, for each school, I generate a strict random priority ordering over all students. Preferences and priorities are independently and uniformly drawn, so there is no systematic bias favoring any student or school.

This setup produce a symmetric and balanced random market environment, which serves as the basis for comparing the performance of different matching mechanisms in subsequent parts.

Part 2

== DA (Deferred Acceptance) (student -> school) ==

i1 -> s2

i2 -> s1

i3 -> s3

i4 -> s1

i5 -> s2

i6 -> s1

i7 -> s1

i8 -> s3

i9 -> s3

i10 -> s1

i11 -> s2

i12 -> s1

i13 -> s2

i14 -> s2

i15 -> s2

i16 -> s3

i17 -> s3

i18 -> s3

Counts: {'s1': 6, 's2': 6, 's3': 6, 'unassigned': 0}

Student	Assigned school
I1	S2
I2	S1
I3	S3
I4	S1
I5	S2
I6	S1
I7	S1
I8	S3
I9	S3
I10	S1
I11	S2
I12	S1
I13	S2
I14	S2
I15	S2
I16	S3
I17	S3
I18	S3

== IA (Immediate Acceptance / Boston) (student -> school) ==

i1 -> s3

i2 -> s1

i3 -> s3

i4 -> s1

i5 -> s2

i6 -> s1

i7 -> s1

i8 -> s2

i9 -> s3

i10 -> s1

i11 -> s2

i12 -> s1

i13 -> s2

i14 -> s2

i15 -> s2

i16 -> s3

i17 -> s3

i18 -> s3

Counts: {'s1': 6, 's2': 6, 's3': 6, 'unassigned': 0}

Student	Assigned school
I1	S3
I2	S1
I3	S3
I4	S1
I5	S2
I6	S1
I7	S1
I8	S2
I9	S3
I10	S1
I11	S2
I12	S1
I13	S2
I14	S2
I15	S2
I16	S3
I17	S3
I18	S3

==== TTC (Top Trading Cycles) (student -> school) ===

i1 -> s1

i2 -> s1

i3 -> s3

i4 -> s1

i5 -> s2

i6 -> s2

i7 -> s1

i8 -> s2

i9 -> s3

i10 -> s1

i11 -> s2

i12 -> s1

i13 -> s2

i14 -> s2

i15 -> s3

i16 -> s3

i17 -> s3

i18 -> s3

Counts: {'s1': 6, 's2': 6, 's3': 6, 'unassigned': 0}

Student	Assigned school
I1	S1
I2	S1
I3	S3
I4	S1
I5	S2
I6	S2
I7	S1
I8	S2
I9	S3
I10	S1
I11	S2
I12	S1
I13	S2
I14	S2
I15	S3
I16	S3
I17	S3
I18	S3

From above, we can see all three mechanisms (DA, IA and TTC) generate feasible matchings. In each case, every school fills its capacity of six seats, and no student remains unassigned.

Part3

==== Part 3: Efficiency Analysis (Average Student Rank) ===

Mechanism | Average Rank (lower is better)

DA		1.2128
IA		1.1823
TTC		1.1938

Mechanism	Average Rank
DA	1.2128
IA	1.1823
TTC	1.1938

Interpretation hint:

- Lower average rank means students, on average, receive more-preferred schools.

- In this simulation, IA has the lowest average rank (best for students by this metric).

Across 1,000 random markets, all three mechanisms yield average ranks close to 1, meaning that in this environment students typically receive one of their top choices. Among the three, IA has the lowest average rank, followed by TTC and DA, indicating that IA produces slightly more preferred assignments for students by this rank-based metric in our simulated random setting.