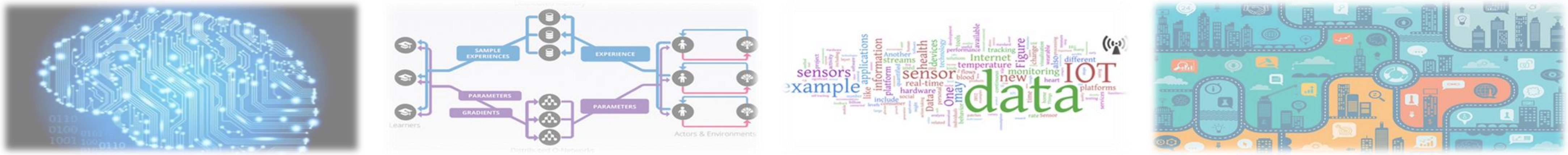

Music Dataset classification

AutoML 연구실
석사 과정 조성현
21.05.25

Dataset statistics of single label - 900 features

Dataset	Patterns	Features		# of Classes	Average Patterns per Class ± Standard Deviation	Domain	길이 구분
		Size	Type				
GTZAN	1000	888	Numeric	10	100.000 ± 0.000	Genre	30s
HOMBURG	1886	888	Numeric	9	209.556 ± 134.866	Genre	10s
FMA_SMALL	7996	888	Numeric	8	999.500 ± 0.500	Genre	30s
MER500	493	888	Numeric	5	98.600 ± 2.332	Emotion	30s ± 30s
emoMusic	1000	888	Numeric	8	125.000 ± 0.000	Emotion	45s
Soundtracks	470	884	Numeric	9	52.222 ± 19.876	Emotion	24s ± 14s
Emotifymusic	400	888	Numeric	4	100.000 ± 0.000	Genre	43 ± 18s
Ballroom	698	888	Numeric	8	87.250 ± 17.555	Genre	30s
SeyerlehnerUnique	3115	888	Numeric	10	311.500 ± 248.349	Genre	30s
MIREX-like_mood	903	884	Numeric	28	32.250 ± 4.778	Mood	30s
Medley-solos	21571	873	Numeric	8	2537.875 ± 2016.080	Instrument	3s
ISMIR04	727	-	Numeric	6	121.167 ± 95.602	Genre	30s
good-sounds	8399	865	Numeric	5	549.400 ± 198.697	Instrument	9s ± 9s
MICM	1137	888	Numeric	7	162.429 ± 119.717	Modal System	6m ± 6m
Tropical Genres	1500	888	Numeric	5	300.000 ± 0.000	Genre	30s
PCMIR	2410	886	Numeric	6	401.667 ± 46.241	Instrument	5s
extendedBallroom	4180	888	Numeric	13	321.538 ± 195.702	Genre	2m ± 2m
giantsteps_tempo	664	888	Numeric	23	28.870 ± 31.872	Tempo	1m30s ± 30s
giantsteps_key	604	888	Numeric	24	25.167 ± 20.418	Key	1m20s ± 40s
GMD	1042	888	Numeric	18	57.889 ± 70.069	Genre	5m ± 5m
FMA_MEDIUM	24984	888	Numeric	16	1561.500 ± 2069.356	Genre	30s
IRMAS	6700	-	Numeric	5	-	Instrument	2s
MagnaTagATune_emotion	25860	888	Numeric	17	-	Emotion	30s
MagnaTagATune_genre	25860	888	Numeric	58	-	Genre	30s
MagnaTagATune_top50	25860	888	Numeric	45	-	Instrument	30s
MagnaTagATune	25860	888	Numeric	9	-	Tempo	30s
CAL500_emotion	498	1277	Numeric	27	-	Emotion	11m ± 11m
CAL500_instrument&vocal	482	888	Numeric	14	-	Instrument&Vocal	11m ± 11m
CAL500_genre	449	888	Numeric	12	-	Genre	11m ± 11m

Dataset statistics of single label - 400 features

Dataset	Patterns	Features		# of Classes	Average Patterns per Class ± Standard Deviation	Domain	길이 구분
		Size	Type				
GTZAN	1000	389	Numeric	10	100.000 ± 0.000	Genre	30s
HOMBURG	1886	389	Numeric	9	209.556 ± 134.866	Genre	10s
FMA_SMALL	7996	389	Numeric	8	999.500 ± 0.500	Genre	30s
MER500	493	389	Numeric	5	98.600 ± 2.332	Emotion	30s ± 30s
emoMusic	1000	389	Numeric	8	125.000 ± 0.000	Emotion	45s
Soundtracks	470	389	Numeric	9	52.222 ± 19.876	Emotion	24s ± 14s
Emotifymusic	400	389	Numeric	4	100.000 ± 0.000	Genre	43 ± 18s
Ballroom	698	389	Numeric	8	87.250 ± 17.555	Genre	30s
SeyerlehnerUnique	3115	389	Numeric	10	311.500 ± 248.349	Genre	30s
MIREX-like_mood	903	385	Numeric	28	32.250 ± 4.778	Mood	30s
Medley-solos	-	-	Numeric	8	2537.875 ± 2016.080	Instrument	3s
ISMIR04	727	389	Numeric	6	121.167 ± 95.602	Genre	30s
good-sounds	8399	371	Numeric	5	549.400 ± 198.697	Instrument	9s ± 9s
MICM	1137	389	Numeric	7	162.429 ± 119.717	Modal System	6m ± 6m
Tropical Genres	1500	389	Numeric	5	300.000 ± 0.000	Genre	30s
PCMIR	2410	387	Numeric	6	401.667 ± 46.241	Instrument	5s
extendedBallroom	4180	389	Numeric	13	321.538 ± 195.702	Genre	2m ± 2m
giantsteps_tempo	664	389	Numeric	23	28.870 ± 31.872	Tempo	1m30s ± 30s
giantsteps_key	604	389	Numeric	24	25.167 ± 20.418	Key	1m20s ± 40s
GMD	1042	-	Numeric	18	57.889 ± 70.069	Genre	5m ± 5m
FMA_MEDIUM	24984	389	Numeric	16	1561.500 ± 2069.356	Genre	30s
IRMAS	6700	-	Numeric	5	-	Instrument	2s
MagnaTagATune_emotion	25860	-	Numeric	17	-	Emotion	30s
MagnaTagATune_genre	25860	-	Numeric	58	-	Genre	30s
MagnaTagATune_top50	25860	-	Numeric	45	-	Instrument	30s
MagnaTagATune	25860	-	Numeric	9	-	Tempo	30s
CAL500_emotion	498	-	Numeric	27	-	Emotion	11m ± 11m
CAL500_instrument&vocal	482	-	Numeric	14	-	Instrument&Vocal	11m ± 11m
CAL500_genre	449	-	Numeric	12	-	Genre	11m ± 11m

Experimental settings(KNN/NB)-900 features

Dataset	KNN(standardize=1)	NB + laim
GTZAN	0.5980 ± 0.0302	**0.7120 ± 0.0218**
HOMBURG	0.2133 ± 0.0244	**0.2761 ± 0.0155**
FMA_SMALL	**0.2193 ± 0.0085**	0.1882 ± 0.0110
MER500	0.4949 ± 0.0417	**0.7214 ± 0.0363**
emoMusic	0.1610 ± 0.0288	**0.2970 ± 0.0193**
Soundtracks	0.1528 ± 0.0365	**0.4306 ± 0.0477**
Emotifymusic	0.6250 ± 0.0559	**0.7275 ± 0.0381**
Ballroom	0.5065 ± 0.0324	**0.7525 ± 0.0451**
SeyerlehnerUnique	**0.6116 ± 0.0194**	0.6031 ± 0.0152
MIREX-like_mood	0.0583 ± 0.0142	**0.1728 ± 0.0335**
Medley-solos	**0.9164 ± 0.0057**	0.7484 ± 0.0030
ISMIR04	-	-
good-sounds	**0.1068 ± 0.0053**	0.0833 ± 0.0073
MICM	0.0714 ± 0.0149	0.0758 ± 0.0205
Tropical Genres	0.9130 ± 0.0190	**0.9160 ± 0.0102**
PCMIR	0.7618 ± 0.0183	**0.7772 ± 0.0163**
extendedBallroom	0.3754 ± 0.1143	**0.5311 ± 0.0199**
giantsteps_tempo	**0.1788 ± 0.0301**	0.0523 ± 0.0610
giantsteps_key	0.0625 ± 0.0201	**0.1267 ± 0.0500**
GMD	**0.2139 ± 0.0144**	0.1851 ± 0.0261
FMA_MEDIUM	**0.5426 ± 0.0058**	0.4653 ± 0.0075
IRMAS	-	-
MagnaTagATune_emotion	-	-
MagnaTagATune_genre	-	-
MagnaTagATune_top50	-	-
MagnaTagATune	-	-
CAL500_emotion	-	-
CAL500_instrument&vocal	-	-
CAL500_genre	-	-

- Overall Settings
  - 8:2 hold-out cross validation
  - “NaN” values were treated by KNN Imputer
  - Datasets consists of 900 under features
  - Experiment Iterations = 10
- KNN settings
  - KNN classifier (k=3)
- NB settings
  - Numeric type of datasets were dicretized by using laim discretization algorithm

Experimental settings(KNN/NB)-400 features

Dataset	KNN(standardize)	NB + laim
GTZAN	0.5980 ± 0.0304	**0.7220 ± 0.0270**
HOMBURG	0.4194 ± 0.0231	**0.4645 ± 0.0243**
FMA_SMALL	0.4621 ± 0.0150	**0.4716 ± 0.0107**
MER500	0.4582 ± 0.0286	**0.7837 ± 0.0339**
emoMusic	0.2105 ± 0.0332	**0.3325 ± 0.0399**
Soundtracks	0.2223 ± 0.0390	**0.3436 ± 0.0420**
Emotifymusic	0.6388 ± 0.0356	**0.7100 ± 0.0337**
Ballroom	0.5129 ± 0.0408	**0.8158 ± 0.0212**
SeyerlehnerUnique	0.6019 ± 0.0168	**0.6504 ± 0.0197**
MIREX-like_mood	0.0567 ± 0.0110	**0.1828 ± 0.0289**
Medley-solos	**0.8985 ± 0.0056**	0.7665 ± 0.0063
ISMIR04	**0.7814 ± 0.0309**	0.7593 ± 0.0235
good-sounds	**0.1070 ± 0.0054**	0.0818 ± 0.0055
MICM	0.0678 ± 0.0140	**0.0996 ± 0.0321**
Tropical Genres	0.9290 ± 0.0187	**0.9317 ± 0.0149**
PCMIR	0.7089 ± 0.0207	**0.7938 ± 0.0101**
extendedBallroom	0.5812 ± 0.0169	**0.7898 ± 0.0145**
giantsteps_tempo	0.1621 ± 0.0650	**0.1909 ± 0.0509**
giantsteps_key	0.0700 ± 0.0292	**0.0817 ± 0.0584**
GMD	**0.2803 ± 0.0350**	0.2500 ± 0.0572
FMA_MEDIUM	**0.5376 ± 0.0130**	0.4860 ± 0.0045
IRMAS		-
MagnaTagATune_emotion		-
MagnaTagATune_genre		-
MagnaTagATune_top50		-
MagnaTagATune		-
CAL500_emotion		-
CAL500_instrument&vocal		-
CAL500_genre		-

- Overall Settings
  - 8:2 hold-out cross validation
  - “NaN” values were treated by KNN Imputer
  - Datasets consists of 900 under features
  - Experiment Iterations = 10
- KNN settings
  - KNN classifier (k=3)
- NB settings
  - Numeric type of datasets were dicretized by using laim discretization algorithm

Experimental settings(proposed)-900 features

Dataset	proposed
GTZAN	0.7570 ± 0.0303
HOMBURG	0.3117 ± 0.0288
FMA_SMALL	0.2014 ± 0.0156
MER500	0.7694 ± 0.0376
emoMusic	0.2880 ± 0.0280
Soundtracks	0.4542 ± 0.0516
Emotifymusic	0.7425 ± 0.0438
Ballroom	0.8367 ± 0.0464
SeyerlehnerUnique	0.6559 ± 0.0192
MIREX-like_mood	0.1700 ± 0.0257
Medley-solos	0.7870 ± 0.0065
ISMIR04	-
good-sounds	0.1999 ± 0.0061
MICM	0.0780 ± 0.0320
Tropical Genres	0.9297 ± 0.0109
PCMIR	0.8201 ± 0.0159
extendedBallroom	0.6349 ± 0.0141
giantsteps_tempo	0.0523 ± 0.0610
giantsteps_key	0.1375 ± 0.0450
GMD	0.2625 ± 0.0263
FMA_MEDIUM	0.5198 ± 0.0088
IRMAS	-
MagnaTagATune_emotion	-
MagnaTagATune_genre	-
MagnaTagATune_top50	-
MagnaTagATune	-
CAL500_emotion	-
CAL500_instrument&vocal	-
CAL500_genre	-

- Overall Settings
  - 8:2 hold-out cross validation
  - “NaN” values were treated by KNN Imputer
  - Datasets consists of 900 under features
  - Experiment Iterations = 10
- NB settings
  - Numeric type of datasets were dicretized by using laim discretization algorithm
- Extract entropy
  - Number of iterations : 10
  - Each score consists of f_ent(single feature entropy), fl_ent(feature-label entropy), ff_ent(feature-feature entropy)
- Proposed
  - Initial population : 50
  - FFCS : 300
  - Initialization : 101 Initialization
  - Evaluation : Naïve Bayes

Comparison - 900 features

Dataset	KNN(standardize=1)	KNN(cosine)	NB + laim	Proposed(knn + relieff)	Proposed(nb + gics)
GTZAN	0.5980 ± 0.0302	0.6385 ± 0.0285	0.7120 ± 0.0218	0.6505 ± 0.0194	**0.7570 ± 0.0303**
HOMBURG	0.2133 ± 0.0244	0.2077 ± 0.0297	0.2761 ± 0.0155	0.2011 ± 0.0289	**0.3117 ± 0.0288**
FMA_SMALL	0.2193 ± 0.0085	**0.2338 ± 0.0081**	0.1882 ± 0.0110	-	0.2014 ± 0.0156
MER500	0.4949 ± 0.0417	0.5449 ± 0.0428	0.7214 ± 0.0363	0.5367 ± 0.0391	**0.7694 ± 0.0376**
emoMusic	0.1610 ± 0.0288	0.1635 ± 0.0201	**0.2970 ± 0.0193**	0.1600 ± 0.0170	0.2880 ± 0.0280
Soundtracks	0.1528 ± 0.0365	0.1972 ± 0.0485	0.4306 ± 0.0477	0.1806 ± 0.0404	**0.4542 ± 0.0516**
Emotifymusic	0.6250 ± 0.0559	0.6975 ± 0.0510	0.7275 ± 0.0381	0.1600 ± 0.0170	**0.7425 ± 0.0438**
Ballroom	0.5065 ± 0.0324	0.5583 ± 0.0327	0.7525 ± 0.0451	0.5799 ± 0.0394	**0.8367 ± 0.0464**
SeyerlehnerUnique	0.6116 ± 0.0194	**0.6595 ± 0.0156**	0.6031 ± 0.0152	0.6542 ± 0.0234	0.6559 ± 0.0192
MIREX-like_mood	0.0583 ± 0.0142	0.0667 ± 0.0176	**0.1728 ± 0.0335**	0.0667 ± 0.0117	0.1700 ± 0.0257
Medley-solos	0.9164 ± 0.0057	**0.9350 ± 0.0030**	0.7484 ± 0.0030	-	0.7870 ± 0.0065
ISMIR04	-	-	-	-	-
good-sounds	0.1068 ± 0.0053	0.1067 ± 0.0054	0.0833 ± 0.0073	-	**0.1999 ± 0.0061**
MICM	0.0714 ± 0.0149	0.0621 ± 0.0159	0.0758 ± 0.0205	0.0648 ± 0.0268	**0.0780 ± 0.0320**
Tropical Genres	0.9130 ± 0.0190	0.9220 ± 0.0164	0.9160 ± 0.0102	**0.9593 ± 0.0165**	0.9297 ± 0.0109
PCMIR	0.7618 ± 0.0183	0.8193 ± 0.0184	0.7772 ± 0.0163	**0.8662 ± 0.0175**	0.8201 ± 0.0159
extendedBallroom	0.3754 ± 0.1143	0.3959 ± 0.1242	0.5311 ± 0.0199	-	**0.6349 ± 0.0141**
giantsteps_tempo	0.1788 ± 0.0301	0.1902 ± 0.0375	0.0523 ± 0.0610	**0.1955 ± 0.0278**	0.0523 ± 0.0610
giantsteps_key	0.0625 ± 0.0201	0.0625 ± 0.0249	0.1267 ± 0.0500	0.0567 ± 0.0235	**0.1375 ± 0.0450**
GMD	0.2139 ± 0.0144	0.2212 ± 0.0181	0.1851 ± 0.0261	0.2115 ± 0.0213	**0.2625 ± 0.0263**
FMA_MEDIUM	0.5426 ± 0.0058	**0.5733 ± 0.0059**	0.4653 ± 0.0075	-	0.5198 ± 0.0088
IRMAS	-	-	-	-	-
MagnaTagATune_emotion	-	-	-	-	-
MagnaTagATune_genre	-	-	-	-	-
MagnaTagATune_top50	-	-	-	-	-
MagnaTagATune	-	-	-	-	-
CAL500_emotion	-	-	-	-	-
CAL500_instrument&vocal	-	-	-	-	-
CAL500_genre	-	-	-	-	-

Accuracies in other papers

1. MICM

TABLE III. DNN RESULTS WITHOUT GRU AND BOTTELNECH

Name of Dastgah	Precision	Recall	F1
Shour	96.35	85.94	90.85
Homayoun	75.34	81.28	78.20
Mahour	90.42	87.12	88.74
Segah	81.79	86.16	83.92
Chahargah	62.23	86.57	72.41
Rastpanjgah	88.06	90.74	89.38
Nava	94.57	86.10	90.14

2. Giantsteps_tempo

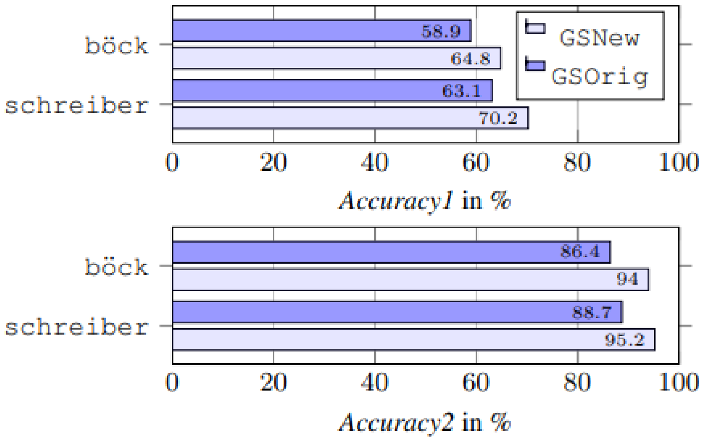

Figure 9: Accuracies for the algorithms böck and schreiber measured against both GSOrig and GSNew.

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Appendix

A review of population initialization techniques for EA

Main goal of those studies are

1. Increase the probability of finding global optima
2. Reduce the variation of final searching results
3. Decrease the computational costs
4. Improve the solution quality

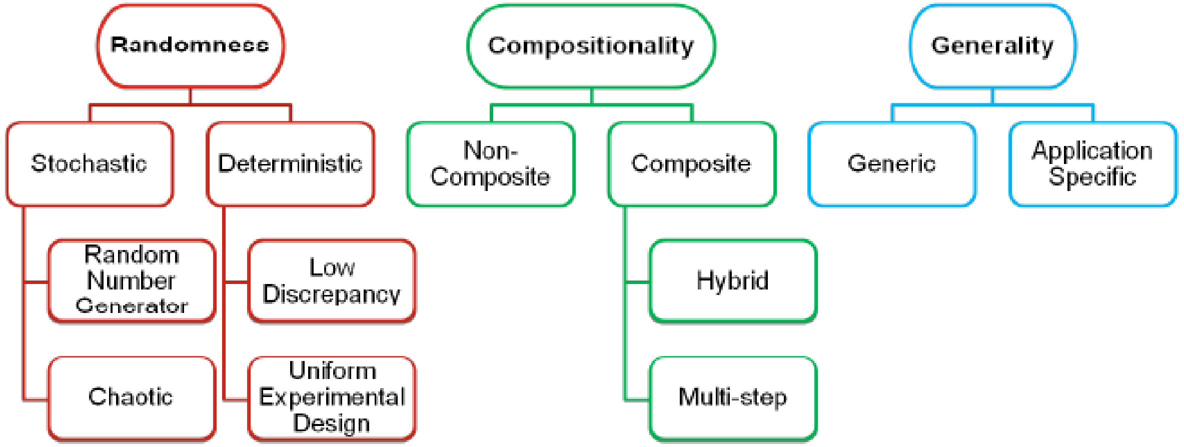


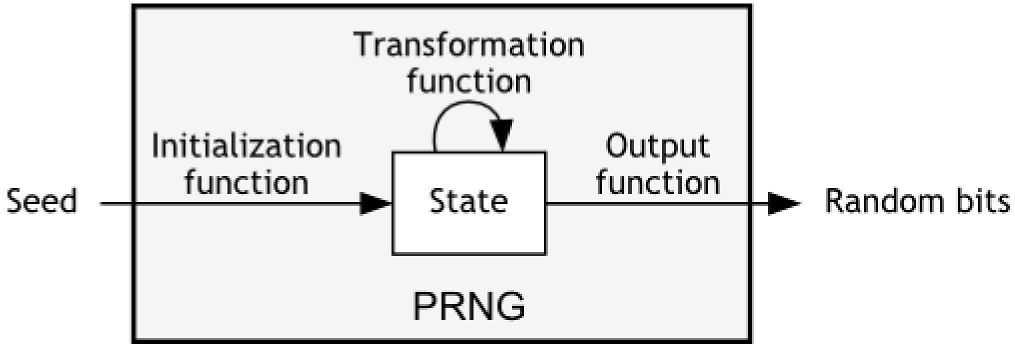
Fig. 1. Three categorizations of population initialization techniques, based on randomness, compositionality and generality.

A review of population initialization techniques for EA

Randomness

Stochastic Technique

- Pseudo-Random Number Generator (PRNG)



- Chaotic Number Generators (CNG)
  - Improve performance in terms of population diversity, success rate, convergence speed

Deterministic Technique(low-discrepancy techniques)

- Quasi-Random Sequence (QRS)
  - Discrepancy calculation > running several EA runs
- Uniform Experimental Design (UED)

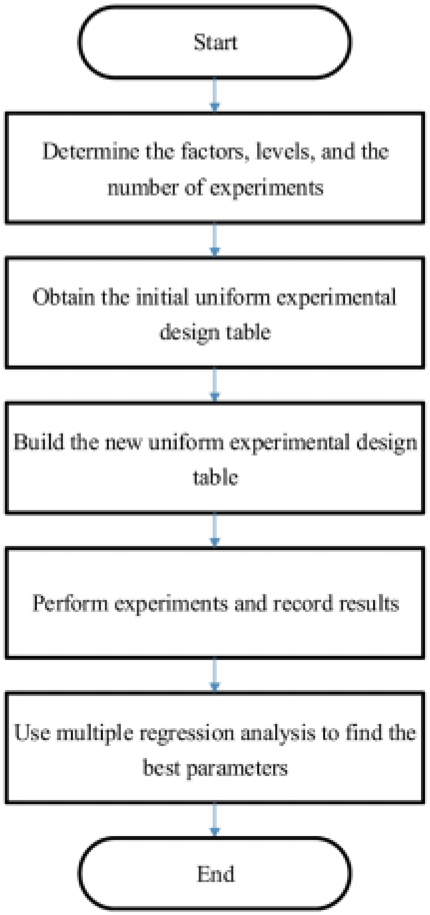


Fig. 2. Flow chart of the UED method.

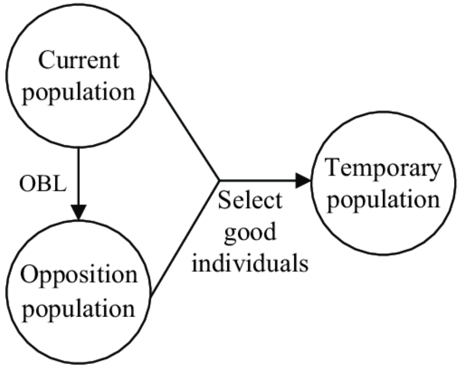
A review of population initialization techniques for EA

Compositionality

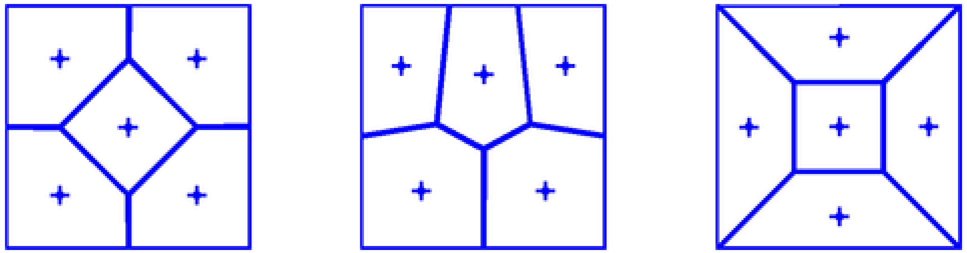
Non-compositional
- Only one single step

Compositional
- Comprise more than one stage
- Hybrid : Separately applied as a non-compositional technique

- Multi-step techniques : At least one of techniques cannot be employed as a standalone initializer
    - Opposition based learning (OBL)



    - Centroidal Voronoi Tessellation (CVT)



A review of population initialization techniques for EA

Generality

- **Generic**
  - Can be directly applied to all types of optimization problems
  - No specific knowledge about the region of interest or building blocks of potential solution is available before running the EA
- **Application Specific**
  - Specially designed to be applied to particular real-world problems