

Morgan_fingerprint_EMBEDDING

December 12, 2025

```
[2]: import pandas as pd

# Read metabolite table
pos = pd.read_csv(
    "m_MTBL8920_LC-MS_positive_hilic_metabolite_profiling_v2_maf.tsv",
    sep="\t"
)

# Extract metabolite + smiles
metabolite_smiles = pos[["database_identifier", "smiles"]].copy()

# Drop missing SMILES
metabolite_smiles = metabolite_smiles.dropna(subset=["smiles"])

# Drop problematic metabolite you already identified
metabolite_smiles = metabolite_smiles[
    metabolite_smiles["database_identifier"] != "CHEBI:172744"
].reset_index(drop=True)

metabolite_smiles.head()
```

```
[2]:   database_identifier                      smiles
 0      CHEBI:28619                         MTBL8920
 1      CHEBI:35807                         CN(C)N=O
 2      CHEBI:41879  C1=CC(C=C2[C@]1([C@@]3([C@@](CC2)([C@]4([C@](C... 
 3      CHEBI:19092                           C1CC=NC1
 4      CHEBI:175520  O1C[C@] (CC=2C1=CC(OC)=C(C2OC)CC=C(C)C) (C3=C4OC...
```

```
[3]: import numpy as np

# sample columns
sample_cols = [
    c for c in pos.columns
    if c.startswith("Breast_") or c.startswith("control_")
]

# abundance: sample x metabolite_id
```

```

abundance = pos.set_index("database_identifier")[sample_cols].T
abundance.index.name = "sample"

# ensure numeric
abundance = abundance.apply(pd.to_numeric, errors="coerce").fillna(0)

print("Abundance shape:", abundance.shape)

```

Abundance shape: (57, 493)

```

[7]: import numpy as np
from sklearn.preprocessing import StandardScaler

abundance_np = abundance.values.astype(float)
abundance_np = np.nan_to_num(abundance_np, nan=0.0)
abundance_np = np.log1p(abundance_np)

scaler_ab = StandardScaler()
abundance_np_scaled = scaler_ab.fit_transform(abundance_np)

abundance_scaled = pd.DataFrame(
    abundance_np_scaled,
    index=abundance.index,
    columns=abundance.columns
)

```

```

[8]: from rdkit import Chem
from rdkit.Chem import AllChem
import numpy as np

# Morgan fingerprint parameters
FP_DIM = 2048
RADIUS = 2

morgan_dict = {}

for _, row in metabolite_smiles.iterrows():
    met_id = row["database_identifier"]
    smi = row["smiles"]

    mol = Chem.MolFromSmiles(smi)
    if mol is None:
        continue

    fp = AllChem.GetMorganFingerprintAsBitVect(
        mol,
        radius=RADIUS,

```

```
nBits=FP_DIM  
)  
  
morgan_dict[met_id] = np.array(fp, dtype=np.float32)  
  
print("Metabolites with Morgan FP:", len(morgan_dict))
```


Metabolites with Morgan FP: 444

```
[03:28:00] DEPRECATION WARNING: please use MorganGenerator
```



```
[9]: valid_mets = [m for m in abundance_scaled.columns if m in morgan_dict]

abundance_final = abundance_scaled[valid_mets]

print("Metabolites used:", len(valid_mets))
```

Metabolites used: 444

```
[10]: sample_embeddings = {}

for sample in abundance_final.index:
    emb_vec = np.zeros(FP_DIM, dtype=np.float32)

    for met in valid_mets:
        weight = abundance_final.loc[sample, met] # normalized abundance
```

```

    emb = morgan_dict[met]                                # Morgan FP
    emb_vec += weight * emb

    sample_embeddings[sample] = emb_vec

```

```
[12]: import pandas as pd

meta_3 = pd.read_csv("s_MTBL8920.txt", sep="\t")

meta_clean_3 = meta_3[~meta_3["Sample Name"].str.startswith("QC")].copy()

meta_ml_3 = meta_clean_3[["Sample Name", "Factor Value[Disease]"]].copy()

meta_ml_3 = meta_ml_3.rename(columns={
    "Sample Name": "sample",
    "Factor Value[Disease]": "disease"
})

meta_ml_3["label"] = meta_ml_3["disease"].map({
    "breast cancer": 1,
    "healthy control": 0
})
```

```
[13]: # sample x fingerprint
sample_embed_df = pd.DataFrame.from_dict(
    sample_embeddings,
    orient="index"
)
sample_embed_df.index.name = "sample"

# merge label
morgan_abundance_ML = sample_embed_df.merge(
    meta_ml_3[["sample", "label"]],
    on="sample",
    how="inner"
)

morgan_abundance_ML
```

```
[13]:      sample      0      1      2      3      4      5  \
0  Breast_1 -1.577821 -63.771938 2.519383 0.0  3.617110 2.881479
1  Breast_10 -0.462907 -131.428162 -1.773262 0.0 -0.264680 -1.044455
2  Breast_11 -0.058059  59.832901 1.802125 0.0  4.642465 -0.187619
3  Breast_12 -0.001556 -75.632179 -0.360007 0.0 -0.747738 -2.223782
4  Breast_13  0.522558 -99.677444 -1.207039 0.0 -3.705719 -2.221539

      6      7      8 ...     2039     2040     2041     2042  \

```

```

0 -0.578136 -1.131751 -14.571426 ... -1.525499 0.619345 -7.009365 0.480932
1 -3.338238 -2.205090 -12.198885 ... -2.123830 0.118527 -2.376938 -1.840528
2 -1.414549 -3.552037 -1.582109 ... -1.892688 1.364370 -1.210879 -2.946210
3 -0.968055 -1.586803 -8.690717 ... -0.696032 1.509288 -0.605615 -3.349327
4 -2.981936 -4.464425 -19.646568 ... -2.021634 0.362182 -2.012872 -2.203544

```

	2043	2044	2045	2046	2047	label
0	0.0	-1.841229	-0.770367	0.0	0.0	1
1	0.0	1.806760	-0.984125	0.0	0.0	1
2	0.0	-0.358407	-1.337365	0.0	0.0	1
3	0.0	-1.091852	3.288409	0.0	0.0	1
4	0.0	-0.237049	1.347519	0.0	0.0	1

[5 rows x 2050 columns]

```
[19]: nonzero_cols = (morgan_abundance_ML != 0).any(axis=0)
```

```
morgan_abundance_ML = morgan_abundance_ML.loc[:, nonzero_cols]
morgan_abundance_ML
```

```
[19]:      sample      0      1      2      4      5      6 \
0    Breast_1 -1.577821 -63.771938 2.519383 3.617110 2.881479 -0.578136
1    Breast_10 -0.462907 -131.428162 -1.773262 -0.264680 -1.044455 -3.338238
2    Breast_11 -0.058059  59.832901 1.802125 4.642465 -0.187619 -1.414549
3    Breast_12 -0.001556 -75.632179 -0.360007 -0.747738 -2.223782 -0.968055
4    Breast_13  0.522558 -99.677444 -1.207039 -3.705719 -2.221539 -2.981936
5    Breast_14 -0.377028 -80.549370 0.523497 0.415671 -2.513501 -2.294846
6    Breast_15  1.319680  69.906898 0.385082 -1.178573 0.971266 0.304147
7    Breast_16  1.198593  30.092297 0.894240 2.330965 2.540152 0.504328
8    Breast_17  0.323576 -11.748161 -0.108333 -0.279216 -0.562423 -1.027992
9    Breast_18  0.161067 -21.364115 -1.977934 -1.733437 -0.819895 0.656544
10   Breast_19 -0.129791 -93.801315 0.092601 -1.809084 -0.358170 -0.964259
11   Breast_2 -0.355148 -102.375092 -0.353270 1.284684 1.780886 -2.087765
12   Breast_20  0.405727 -92.887711 -3.368630 -3.529855 -0.825127 -1.571842
13   Breast_21  0.192209 -121.396484 -2.775005 -2.959791 -1.016257 0.124716
14   Breast_22  0.248085  39.961792 0.021861 0.960442 2.570335 0.901591
15   Breast_23  1.445831  23.489885 5.543217 0.987101 8.335752 0.068494
16   Breast_24  1.223900 -59.378506 -1.136493 -2.523135 -0.995864 0.473622
17   Breast_25 -0.517244 -31.619402 -0.197218 -3.222729 3.392680 -0.375715
18   Breast_26  0.454824  128.776215 1.935286 -3.138026 3.768036 1.291131
19   Breast_27  0.522346 -193.339523 -4.138151 -2.873491 -2.878180 -2.191990
20   Breast_28  0.024950  60.777237 -0.988702 1.592048 -2.017148 0.736357
21   Breast_3 -0.005455 -71.673767 0.048156 -2.071554 -1.885629 -1.738357
22   Breast_4  0.827522 -42.707882 -1.475319 0.554141 1.752407 1.004571
23   Breast_5 -0.097325 -108.588547 -0.335895 0.136871 -2.820122 1.358515
24   Breast_7  0.439780 -17.035620 0.657089 2.373134 -2.140277 -0.660395
25   Breast_8  0.498623 -110.746346 0.487303 -3.546439 -0.097050 -2.070427
```

26	Breast_9	0.506481	-59.494576	-0.078015	-0.242320	1.455656	2.479789
27	control_1	0.344726	17.284214	-0.708481	-1.345473	-1.236349	0.575228
28	control_10	0.159251	40.132339	0.330227	-0.200172	0.905295	0.152785
29	control_11	-0.537176	106.829453	0.822135	0.122445	1.951240	2.054050
30	control_12	0.628927	2.086747	-0.192534	-1.490362	2.925764	-0.786773
31	control_13	-0.228658	155.230728	2.124144	1.717009	2.589468	1.904789
32	control_14	0.621906	10.887565	-1.520953	-1.154276	-1.938136	0.908089
33	control_15	0.145974	77.623772	-1.307395	-0.119290	-3.520546	1.229993
34	control_16	-0.960635	50.664139	1.293004	2.671135	2.932807	1.062628
35	control_17	-0.336467	92.861343	0.398912	0.603929	-0.457083	1.015026
36	control_18	-6.245316	78.397560	1.716001	2.673788	0.110686	0.654185
37	control_19	-0.229567	-47.549133	-0.881512	-3.440107	0.084481	-1.741984
38	control_2	-0.264012	31.794476	1.933762	4.124017	0.589679	1.498574
39	control_20	0.302372	28.694813	-0.406864	3.031134	-0.132642	0.158530
40	control_21	-1.197505	74.020866	0.440664	1.093153	2.041894	-0.774692
41	control_22	-0.075306	-3.122585	1.550893	0.676102	0.040827	-2.029262
42	control_23	0.076952	-6.802446	-1.232931	-0.018436	-2.433636	1.050102
43	control_24	0.614004	-20.279352	-0.516627	-2.199014	-3.231893	-0.931285
44	control_25	0.344809	23.927681	0.624941	-0.795765	-1.189744	1.352253
45	control_26	0.083489	83.022682	1.550425	1.399600	1.354261	3.687218
46	control_27	0.123651	67.629562	-0.086028	0.524495	0.971809	0.548718
47	control_28	-0.058165	25.141212	1.209469	1.359949	0.507893	0.976440
48	control_29	-0.236342	71.019707	-0.462640	3.749186	-1.277605	0.425622
49	control_3	0.167366	-34.797283	0.357245	-0.066158	1.168891	0.177882
50	control_30	-0.643911	-14.000072	1.835436	1.428437	-0.043603	-0.616939
51	control_4	-0.209942	122.459976	-0.920861	2.636191	-0.467058	1.950020
52	control_5	0.216940	70.276794	-0.047402	-0.267109	0.071883	0.603828
53	control_6	-0.079475	40.371067	-0.507461	-0.477919	-1.543805	-0.358059
54	control_7	0.432535	84.358543	0.949899	1.760492	-2.822368	1.914291
55	control_8	-0.063806	14.231878	-1.445765	-1.476629	-1.507881	-0.153884
56	control_9	0.369962	-66.017410	-1.536271	-1.589195	-1.286143	-2.146675

	7	8	9	...	2035	2037	2038	\
0	-1.131751	-14.571426	-1.861321	...	0.406672	0.184906	25.807522	
1	-2.205090	-12.198885	-0.352454	...	-1.560328	0.717220	-3.868195	
2	-3.552037	-1.582109	-0.670278	...	-2.544272	-0.683314	18.354477	
3	-1.586803	-8.690717	0.951084	...	-1.227247	0.302983	-12.904033	
4	-4.464425	-19.646568	0.079340	...	-4.855191	-1.832383	-6.097253	
5	-2.822525	-11.954848	1.077436	...	-0.002535	0.119448	0.092159	
6	0.287346	-1.421384	-1.366856	...	3.441972	1.117718	15.763485	
7	0.647401	-3.597660	-0.897405	...	2.745557	-2.432338	3.358941	
8	-1.954207	-5.068198	1.349519	...	-3.706210	0.801929	-6.272098	
9	-1.094090	0.861966	0.347395	...	-2.409920	0.340438	9.668518	
10	-1.136406	-6.359642	0.955487	...	-1.318173	0.332667	-14.074587	
11	-2.096948	-8.931929	0.938213	...	-1.724004	0.297168	-1.711162	
12	-0.638754	0.266889	1.311957	...	-0.475437	0.390245	-6.970936	
13	-1.978605	0.298321	-0.181288	...	-0.988314	0.346313	-13.934760	

14	2.989360	5.116446	0.592651	...	1.114378	0.228223	10.715270
15	1.273390	4.367759	0.654822	...	-0.701211	0.804361	-19.601755
16	-1.055286	-8.479153	0.164643	...	1.049131	0.323292	-9.187586
17	-1.349630	0.653174	-0.280863	...	-1.653756	-0.849220	0.708098
18	-0.287695	7.340446	-1.620130	...	-2.325716	-1.050491	14.312077
19	-4.603915	-3.069319	2.413633	...	-3.113409	1.228905	-21.041458
20	2.987509	7.931948	0.137618	...	0.291863	0.438107	12.622253
21	-2.747367	-12.064553	-0.692529	...	1.308026	0.353445	3.849181
22	0.061767	2.212223	-0.322633	...	-1.878157	1.129786	-9.621005
23	1.353153	-8.992580	0.619826	...	3.365197	0.286943	0.016523
24	3.915261	1.297010	-0.122544	...	-0.060711	0.241144	-2.035032
25	-1.047273	-12.026852	2.107308	...	1.214462	-1.584782	0.239402
26	3.639369	2.065905	-1.196867	...	1.829335	0.319605	-5.941478
27	1.133942	4.150527	-2.790581	...	-1.494848	0.102815	1.355160
28	-3.869670	-2.830388	0.565865	...	-1.215553	0.594764	11.332007
29	4.664620	9.840240	-0.973511	...	1.617748	-0.410882	18.159657
30	-2.905175	5.176883	-0.289854	...	-1.215137	-0.271957	-8.111947
31	-0.548172	11.652799	-1.127933	...	-0.223871	0.259768	14.684847
32	1.793109	5.839436	-0.598026	...	2.084352	0.397427	-1.600280
33	2.242677	9.566770	-0.238075	...	2.165102	-1.733388	-3.674297
34	0.443357	8.664005	0.374799	...	1.679695	-1.052620	12.478277
35	-0.505418	9.848477	-0.622583	...	4.341630	-2.870811	9.249910
36	-1.239613	2.651411	0.088271	...	-0.131776	0.288727	12.987974
37	0.076592	0.642919	0.329105	...	-1.717374	1.328499	-18.217957
38	2.329894	6.439797	0.953147	...	1.983269	1.065727	-0.180908
39	2.009258	3.419312	1.274807	...	-2.272105	0.287751	-11.898565
40	-0.541657	3.600390	-0.125512	...	-1.326065	0.299974	9.117936
41	-3.878952	-2.323802	0.316967	...	-1.823567	0.296469	-0.920544
42	3.309128	-7.326036	0.973565	...	-0.538256	0.268268	-18.922113
43	-0.180823	-3.996730	-0.335466	...	-0.466858	1.121918	-13.139399
44	0.900903	-0.020428	0.150159	...	0.494123	-0.002509	-0.907416
45	1.650264	4.742365	-0.448791	...	3.536846	0.861965	3.117191
46	-0.135439	2.961195	-0.316009	...	0.179191	-2.023907	9.100789
47	1.485703	0.743416	-0.080703	...	2.448230	0.497622	-10.821836
48	3.277027	12.077893	-1.521274	...	5.266572	1.193347	11.366472
49	-0.444897	-9.310042	1.136533	...	-2.724898	-0.588951	-5.957805
50	-2.275975	3.176654	1.169152	...	1.275269	0.221227	-5.287311
51	5.771136	8.284544	-2.354664	...	2.100912	0.330918	9.033189
52	-0.313221	5.947603	-0.313333	...	0.414689	-1.278962	0.152494
53	2.865170	6.012676	-0.227228	...	2.048009	1.178996	8.447434
54	1.292099	3.270333	0.419287	...	0.756579	0.294694	9.825337
55	1.537149	4.266818	0.081452	...	-0.996916	0.243656	-7.869002
56	-1.344763	-0.925296	0.394672	...	-2.466995	-2.772863	-15.145872

	2039	2040	2041	2042	2044	2045	label
0	-1.525499	0.619345	-7.009365	0.480932	-1.841229	-0.770367	1
1	-2.123830	0.118527	-2.376938	-1.840528	1.806760	-0.984125	1

2	-1.892688	1.364370	-1.210879	-2.946210	-0.358407	-1.337365	1
3	-0.696032	1.509288	-0.605615	-3.349327	-1.091852	3.288409	1
4	-2.021634	0.362182	-2.012872	-2.203544	-0.237049	1.347519	1
5	-4.960733	-0.083534	-2.309518	-1.950238	2.953205	-0.614862	1
6	-1.848888	-0.602811	1.913821	2.543114	-0.462794	0.700600	1
7	0.669057	-0.387292	0.790129	0.113250	0.291465	-0.135850	1
8	-1.540754	0.429791	0.338263	0.375218	2.936503	0.850150	1
9	-0.080603	-0.711015	1.650100	0.728260	2.203407	-0.558213	1
10	-1.277359	1.277176	-1.235959	-2.874829	0.163668	-0.355272	1
11	-1.238571	-1.735411	-2.298757	-0.509185	0.803254	0.907511	1
12	-0.176494	0.430384	2.085759	0.469348	-1.290333	1.220300	1
13	1.554878	2.522246	1.685867	0.119645	-1.331253	0.316728	1
14	0.635167	0.232898	-0.065892	2.921533	-2.556237	-0.022152	1
15	-1.706216	-0.866527	-1.106549	1.781245	-1.129261	0.852984	1
16	1.954600	0.345905	4.136502	1.461302	-1.452394	0.439057	1
17	-1.406832	0.159083	0.840393	-1.944591	-1.460755	-0.643267	1
18	1.251680	-1.175103	0.569067	-1.122405	0.257440	0.719633	1
19	-7.307338	-2.194023	-3.254924	-1.988927	1.917969	-1.890589	1
20	-0.357630	1.779748	1.993150	3.449870	-0.382382	-0.440085	1
21	0.942220	0.888677	1.895064	-1.099630	-0.327086	-0.486317	1
22	-0.890594	0.457218	-0.183446	0.798839	-0.783525	0.212189	1
23	4.062076	0.410181	1.277490	0.719003	3.229269	-1.079710	1
24	0.204375	-1.489290	-2.365291	-3.476831	0.716498	-0.414338	1
25	-0.901431	-1.161160	-1.152193	-2.109130	1.458242	-2.580553	1
26	5.130542	-1.382279	2.854811	2.408052	-1.091843	1.390827	1
27	0.047281	0.134717	-0.790449	0.424735	-2.352363	-0.276436	0
28	0.621902	0.878529	-1.484326	0.168629	-0.103705	-0.003821	0
29	0.566339	-0.458097	-0.682318	1.207550	-0.998093	0.505997	0
30	0.117637	0.985556	0.750336	-0.013471	0.633004	1.060287	0
31	-0.229282	-0.478021	-2.262308	1.946468	-0.017038	1.137515	0
32	1.142318	0.103366	0.422751	0.951039	-2.661158	-0.100720	0
33	3.744782	-0.476126	2.381333	1.317338	0.248268	0.575689	0
34	1.997771	-0.275007	0.079734	0.163391	1.736207	-0.117855	0
35	0.897067	-0.797411	0.910178	3.183214	-1.173505	0.227411	0
36	-0.550152	0.161523	-2.619191	-0.353035	2.970695	0.485959	0
37	-0.392360	2.289821	-2.208766	-3.863082	-3.181592	0.165411	0
38	2.191755	-0.287665	0.660800	-0.481297	2.028596	-1.726705	0
39	-2.253137	-0.829837	0.200065	-2.363508	2.313675	-1.387579	0
40	-0.972172	-1.061687	-2.142606	0.858676	0.759539	-0.412720	0
41	-4.051919	-0.776241	-1.162009	0.594886	-0.142280	0.560845	0
42	-1.099188	-1.249040	-0.929002	0.148090	-0.487398	-2.852219	0
43	0.539770	1.070168	-0.348630	-1.707103	-1.946502	0.812911	0
44	0.755133	0.438451	-1.577958	-0.045895	-0.018299	-0.615549	0
45	1.734670	-0.018837	0.547540	2.848412	-0.739127	1.240845	0
46	-0.357706	0.084153	-1.441937	-0.167291	0.253577	0.254834	0
47	0.539878	-0.411115	6.645276	0.346189	0.784649	0.165318	0
48	3.746002	-2.211902	1.463393	2.688958	1.834320	0.107379	0

```

49 -1.440679  0.245530 -2.717933 -0.090637  0.667261  0.008718  0
50 -0.279829 -1.259002  3.082096  0.110309 -0.340987 -0.506620  0
51  2.811098  0.042105  4.512824  0.704178 -0.403841  0.372538  0
52  0.093633  0.520501 -0.827331  0.248041 -0.144364  0.272101  0
53  3.635352  0.871489  6.499184  0.907421 -1.836129  0.560169  0
54  2.353171  0.327373 -1.450833 -0.053466  0.773353  0.130662  0
55 -0.200318  1.126032 -1.710859  0.285345 -0.635436 -0.541088  0
56 -0.160282  0.192101  1.358729 -0.918320 -0.762609 -0.036119  0

```

[57 rows x 1618 columns]

```

[21]: # -----
# ML Baseline: Morgan + Abundance
# -----


import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import roc_auc_score, roc_curve, confusion_matrix,classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
import matplotlib.pyplot as plt
import seaborn as sns

# -----
# O. Define X, y (FROM morgan_abundance_ML)
# -----
# morgan_abundance_ML columns:
# ['sample', feature_0, ..., feature_2045, 'label']

X = morgan_abundance_ML.drop(columns=["sample", "label"]).values
y = morgan_abundance_ML["label"].values

print("X shape:", X.shape)
print("y shape:", y.shape)

# -----
# 1. Train-test split
# -----
X_train, X_test, y_train, y_test = train_test_split(
    X,
    y,
    test_size=0.2,
    random_state=42,
    stratify=y
)

```

```

)
# -----
# 2. Define models
# -----
models = {
    "Logistic Regression": LogisticRegression(max_iter=500),
    "SVM (RBF kernel)": SVC(kernel="rbf", probability=True),
    "Random Forest": RandomForestClassifier(
        n_estimators=200,
        random_state=42
    )
}

results = {}

# -----
# 3. Train & Evaluate models
# -----
for name, model in models.items():
    print(f"\n====")
    print(f"Training: {name}")
    print("====")

    # Train
    model.fit(X_train, y_train)

    # Predict probability for ROC
    y_prob = model.predict_proba(X_test)[:, 1]

    # Metrics
    auc = roc_auc_score(y_test, y_prob)
    y_pred = model.predict(X_test)

    results[name] = {
        "model": model,
        "auc": auc,
        "confusion_matrix": confusion_matrix(y_test, y_pred),
        "classification_report": classification_report(
            y_test, y_pred, output_dict=False
        )
    }

    print(f"AUC: {auc:.4f}")
    print(results[name]["classification_report"])

#

```

```

# 4. Plot ROC curves
# -----
plt.figure(figsize=(8, 6))

for name, result in results.items():
    model = result["model"]
    y_prob = model.predict_proba(X_test)[:, 1]
    fpr, tpr, _ = roc_curve(y_test, y_prob)

    plt.plot(
        fpr,
        tpr,
        label=f"{name} (AUC={result['auc']:.3f})"
    )

plt.plot([0, 1], [0, 1], "k--")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curves - Morgan + Abundance Models")
plt.legend()
plt.grid(alpha=0.3)
plt.show()

# -----
# 5. Plot confusion matrices
# -----
for name, result in results.items():
    cm = result["confusion_matrix"]

    plt.figure(figsize=(4, 4))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues")
    plt.title(f"Confusion Matrix - {name}")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

# -----
# 6. Cross-validation (5-fold)
# -----
print("\n\n===== 5-fold Cross Validation (Morgan + Abundance) =====")

for name, model in models.items():
    cv_auc = cross_val_score(
        model,
        X,
        y,
        cv=5,

```

```

        scoring="roc_auc"
    )
    print(f"{name} CV AUC: mean={cv_auc.mean():.4f}, std={cv_auc.std():.4f}")

```

X shape: (57, 1616)

y shape: (57,)

=====

Training: Logistic Regression

AUC: 0.8333

	precision	recall	f1-score	support
0	0.71	0.83	0.77	6
1	0.80	0.67	0.73	6
accuracy			0.75	12
macro avg	0.76	0.75	0.75	12
weighted avg	0.76	0.75	0.75	12

=====

Training: SVM (RBF kernel)

AUC: 0.8056

	precision	recall	f1-score	support
0	0.50	0.83	0.62	6
1	0.50	0.17	0.25	6
accuracy			0.50	12
macro avg	0.50	0.50	0.44	12
weighted avg	0.50	0.50	0.44	12

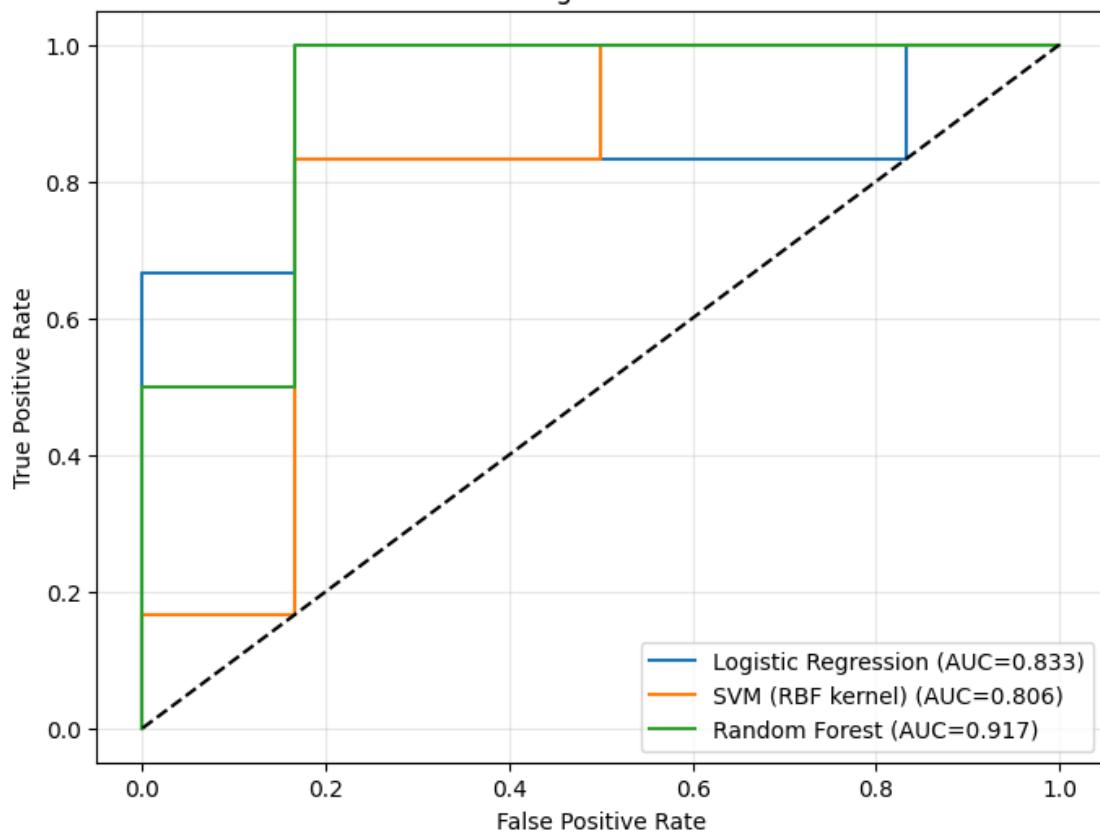
=====

Training: Random Forest

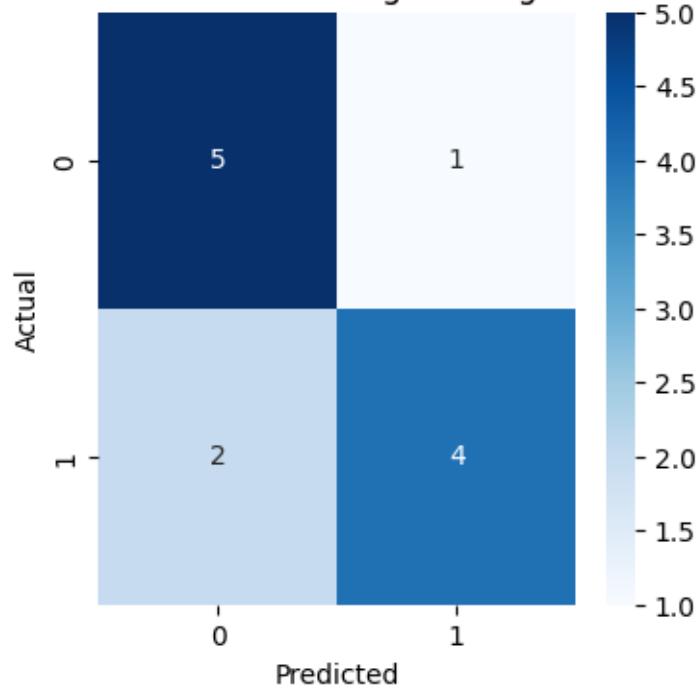
AUC: 0.9167

	precision	recall	f1-score	support
0	0.67	1.00	0.80	6
1	1.00	0.50	0.67	6
accuracy			0.75	12
macro avg	0.83	0.75	0.73	12
weighted avg	0.83	0.75	0.73	12

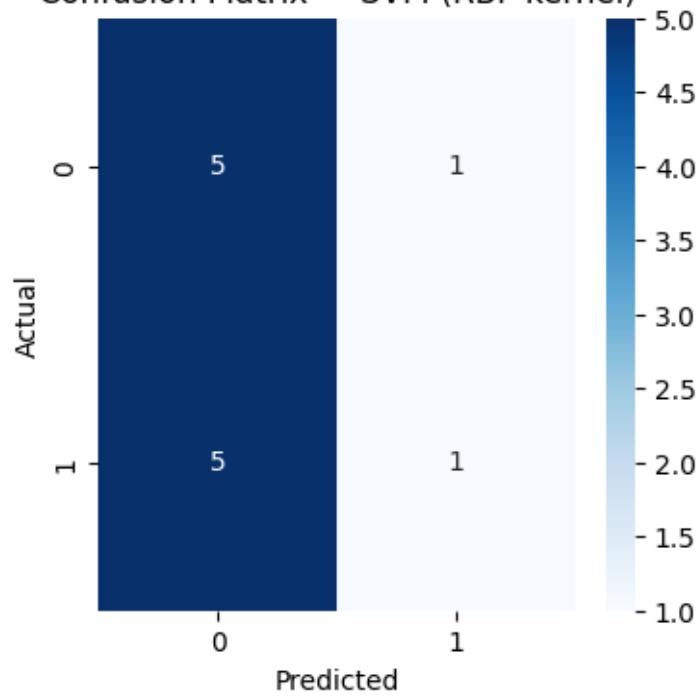
ROC Curves — Morgan + Abundance Models



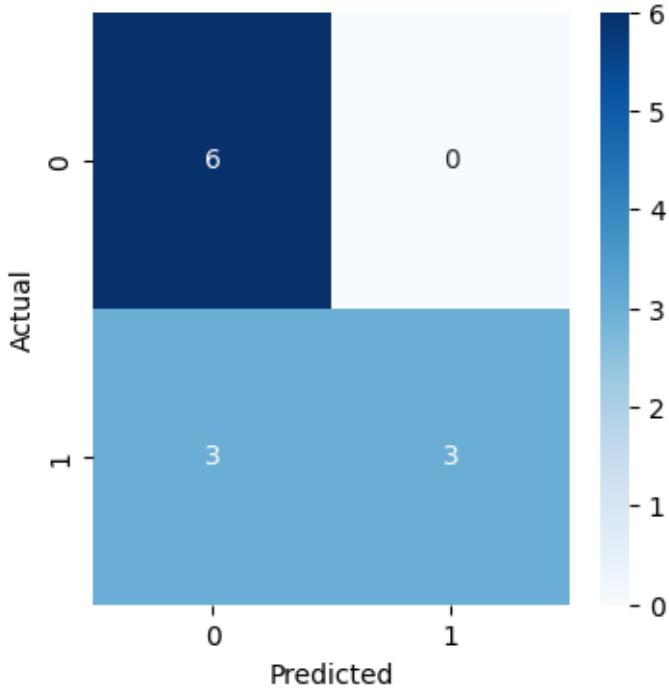
Confusion Matrix — Logistic Regression



Confusion Matrix — SVM (RBF kernel)



Confusion Matrix — Random Forest



===== 5-fold Cross Validation (Morgan + Abundance) =====

Logistic Regression CV AUC: mean=0.8989, std=0.0731

SVM (RBF kernel) CV AUC: mean=0.8111, std=0.0916

Random Forest CV AUC: mean=0.9011, std=0.0861

[]: