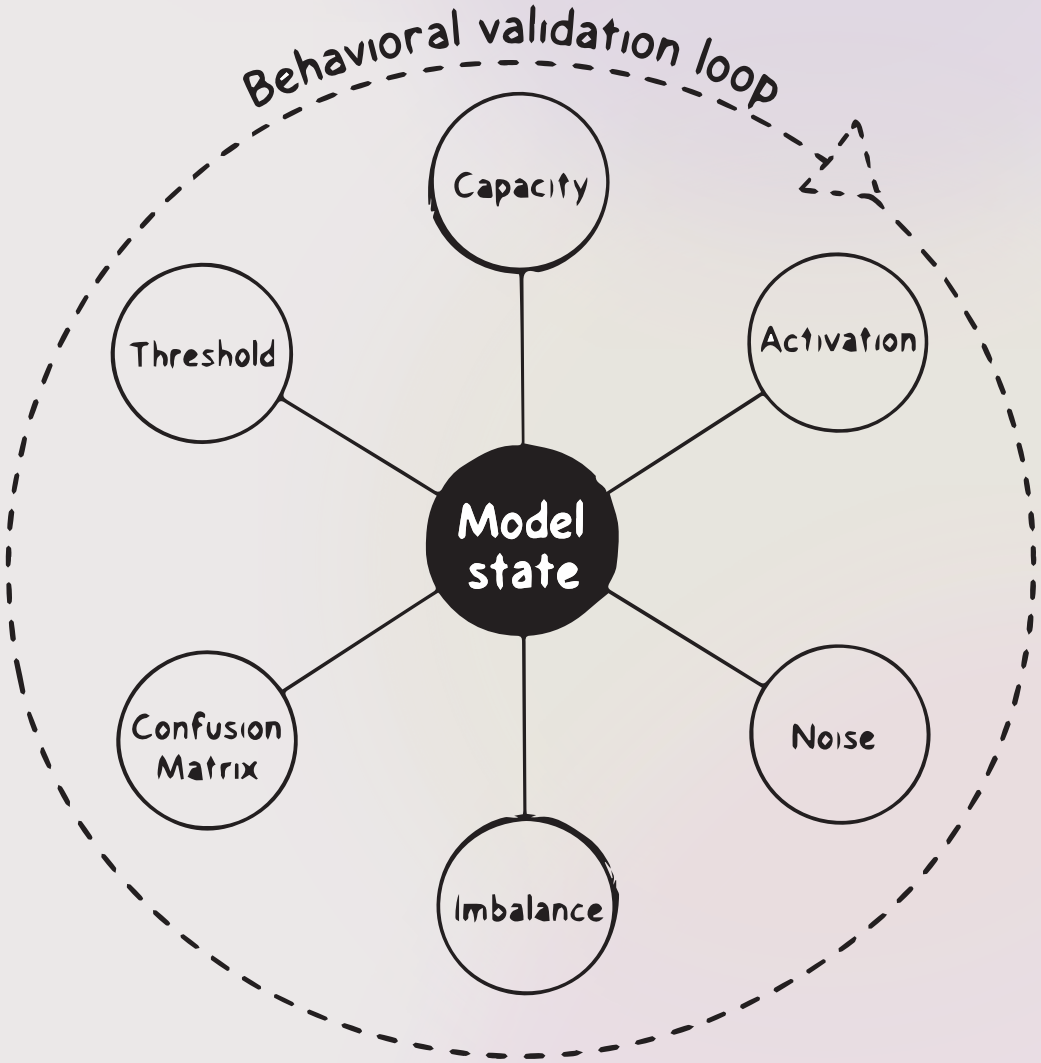
Training Behavior of a Titanic Survival Model



Validation loop

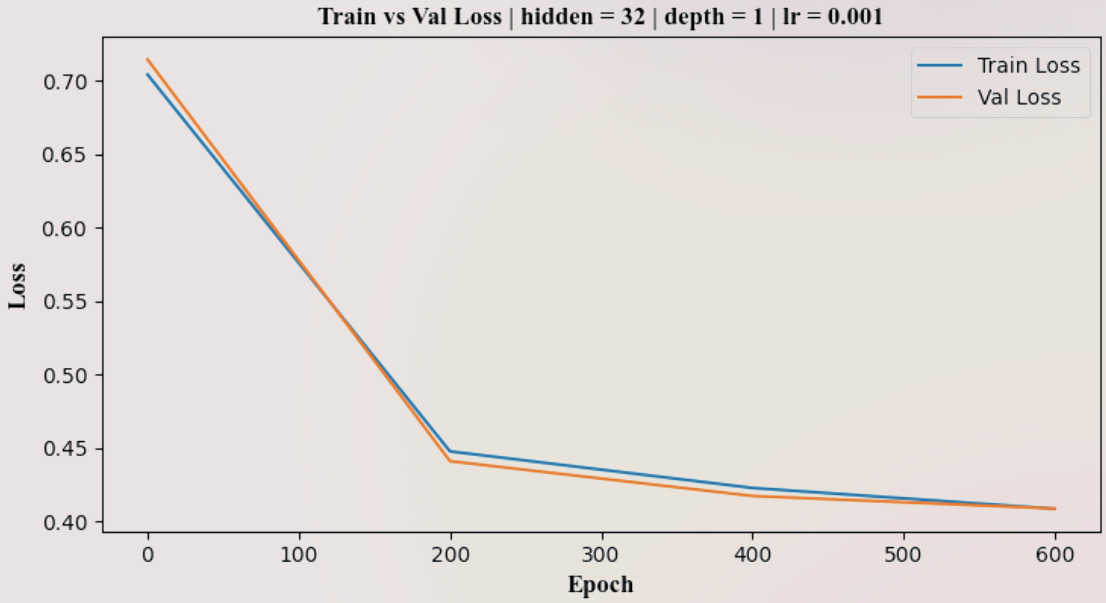
Global settings

SEED = 33
HIDDEN = 32
EPOCHS = 600
TEST_SIZE = 0.2

LR = 1e-3
DEPTH = 1
WEIGHT_DECAY = 1e-4
THRESHOLDS = (0.3, 0.5, 0.8)

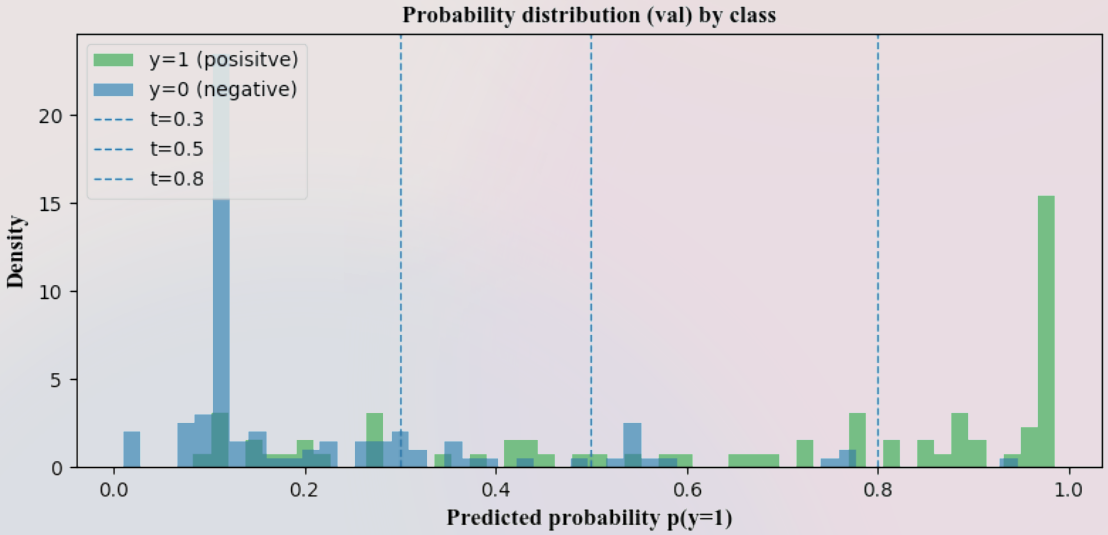
找合適的capacity與depth與epoch，透過probability檢查loss與activation的一致性，檢查logit分佈狀態是否屬於當前sigmoid合適區間段(確保saturation的狀況不會發生)。

Capacity & Depth sweep



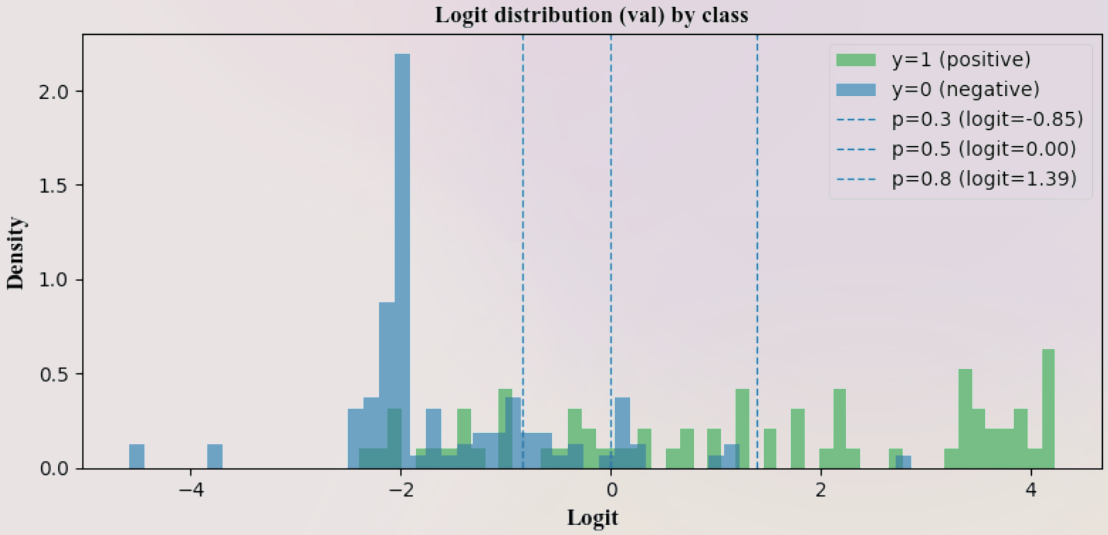
從目前的train loss與validation loss比較，目前的capacity與depth組合呈現收斂狀態。

Probability



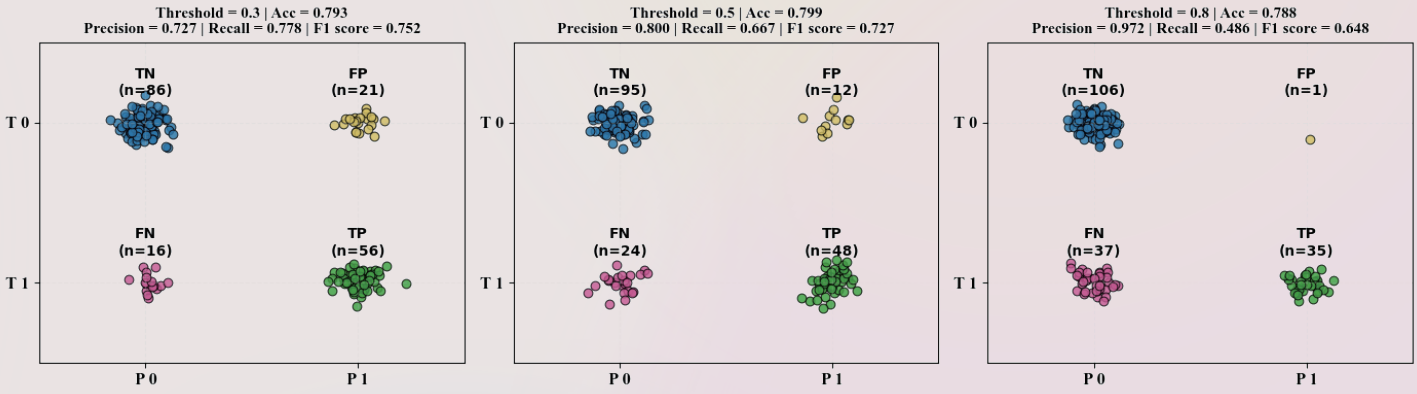
從機率分佈可以觀察，除了明確的positive與negative區域之外，仍存在一段類別重疊的灰色區間（代表目前現有特徵對類別分類能力有限）。透過預先設定的多個threshold可以進一步觀察模型在不同決策門檻下，對於正負類別的信心分級與風險取捨方式。

Logit



同樣從logit分佈可以觀察到，當threshold = 0.3時，分類決策規則改變，使模型傾向於將更多樣本判為positive。且目前有梯度平緩飽和區風險存在

Confusion matrix



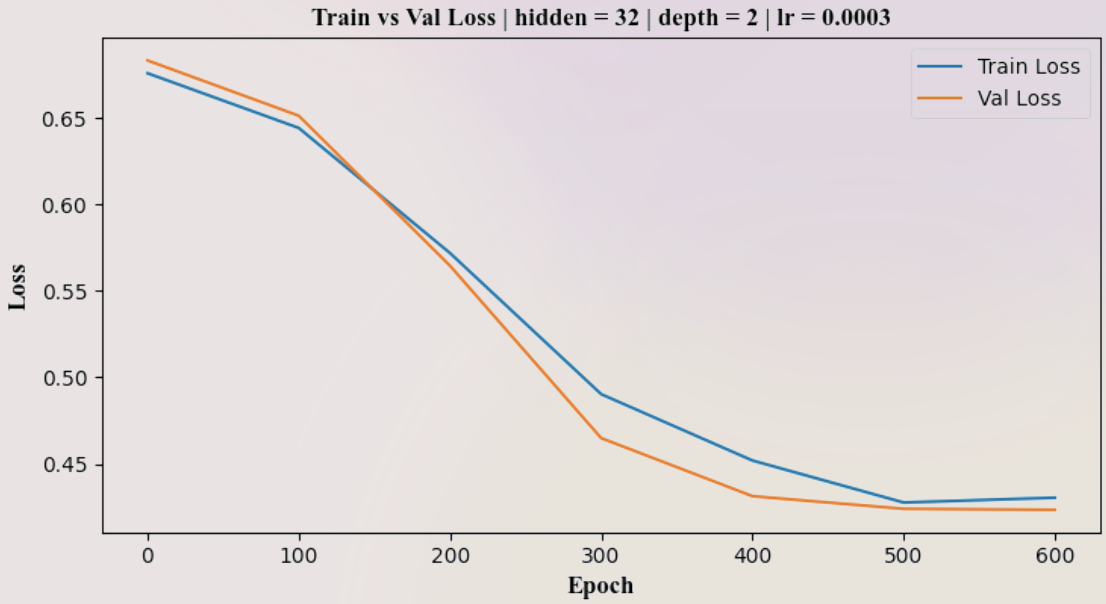
進一步透過confusion matrix得到驗證，在threshold = 0.3的情況下，False negative的數量明顯少於其他決策門檻，顯示模型在此設定下更積極嘗試抓取positive樣本。

然而整體結果仍未達到理想的風險取捨狀態，代表目前特徵組合下，模型在正負類別的可分性仍受限制。因此下一步將嘗試調整feature的組合，以改善logit分佈的分離程度，並重新評估不同threshold下的決策行為。

Global settings(updated)

LR = 3e-4
DEPTH = 2
DROPOUT = 0.3

Feature



透過interaction feature加強關聯性欄位有助於模型提升非線性學習關聯，目前在此條件設定下有良好的學習結構曲線(顯示模型capacity被更有效的利用，而非單純增加複雜度）

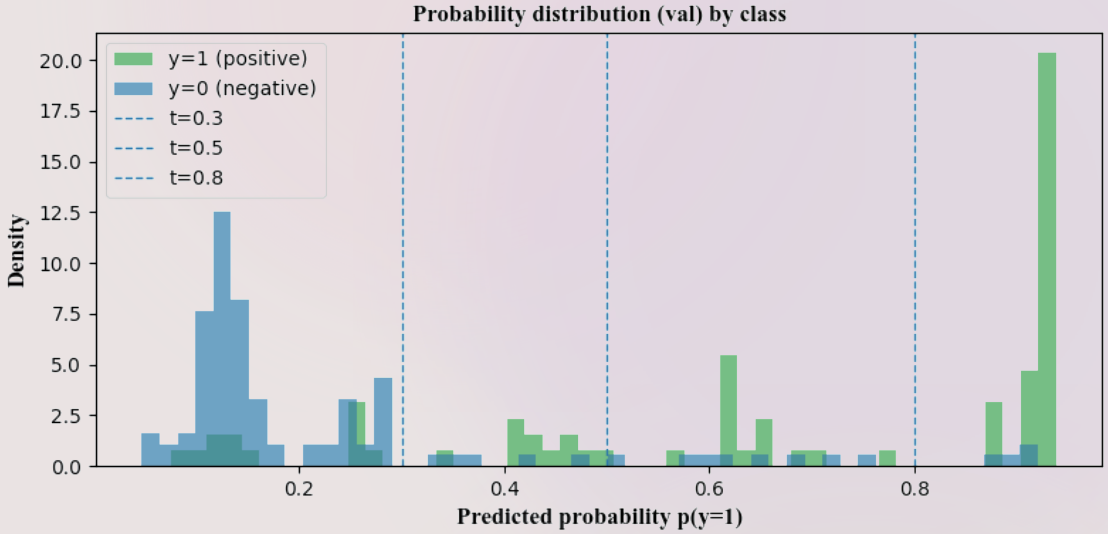
Feature engineering

```
# sex + pclass----------------------------------------------------------------
X_train['Sex_Pclass'] = X_train['Sex'] + '_P' + X_train['Pclass'].astype(str)
X_val['Sex_Pclass'] = X_val['Sex'] + '_P' + X_val['Pclass'].astype(str)
# --Ticket-------------------------------------------------------------------------------
ticket_counts = X_train['Ticket'].value_counts()
X_train['TicketGroupSize'] = X_train['Ticket'].map(ticket_counts).fillna(1).astype(int)
X_val['TicketGroupSize']   = X_val['Ticket'].map(ticket_counts).fillna(1).astype(int)
# ticket group size-----------------------------------------------------------------
bins = [0, 2, 4, float('inf')]
labels = ['solo', 'small', 'medium']
X_train['IsGroupTicket'] = pd.cut(X_train['TicketGroupSize'], bins=bins, labels=labels, include_lowest=True)
X_val['IsGroupTicket'] = pd.cut(X_val['TicketGroupSize'], bins=bins, labels=labels, include_lowest=True)
# fare and group ticket compare-----------------------------------------------------------+
fare_median = X_train['Fare'].median()
X_train['Fare'] = X_train['Fare'].fillna(fare_median)
X_val['Fare'] = X_val['Fare'].fillna(fare_median)
q = np.quantile(X_train['Fare'], [0, 0.25, 0.5, 0.75, 1.0])
q = np.unique(q)
labels = [f"Q{i}" for i in range(len(q)-1)]
X_train['FareBin'] = pd.cut(X_train['Fare'], bins=q, labels=labels, include_lowest=True)
X_val['FareBin']   = pd.cut(X_val['Fare'],   bins=q, labels=labels, include_lowest=True)
# -- compose-----------------------------------------------------------------------
X_train['GroupTicket_Fare'] = 'G' + X_train['IsGroupTicket'].astype(str) + '_' + X_train['FareBin'].astype(str)
X_val['GroupTicket_Fare']   = 'G' + X_val['IsGroupTicket'].astype(str)   + '_' + X_val['FareBin'].astype(str)
# -- input-----------------------------------------------------
num_columns = ['Age']
cat_columns = ['Sex_Pclass', 'GroupTicket_Fare']
```

Feature engineering設計思路

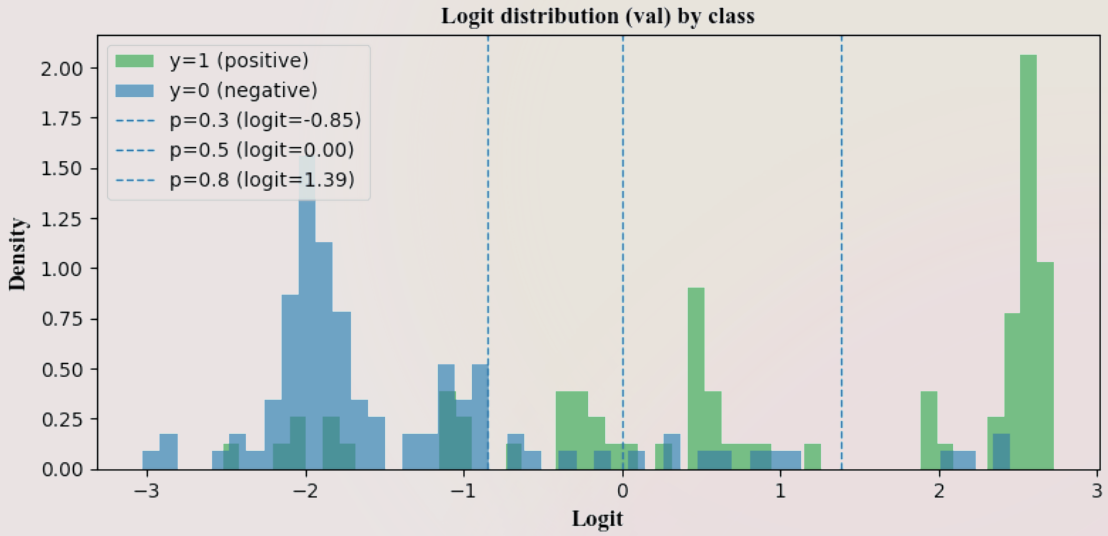
將Sex與Pclass交互，由Fare與Ticket團體票價交互，並將團體總類分為單人、2~4小團、5人以上大團。

Feature × Probability



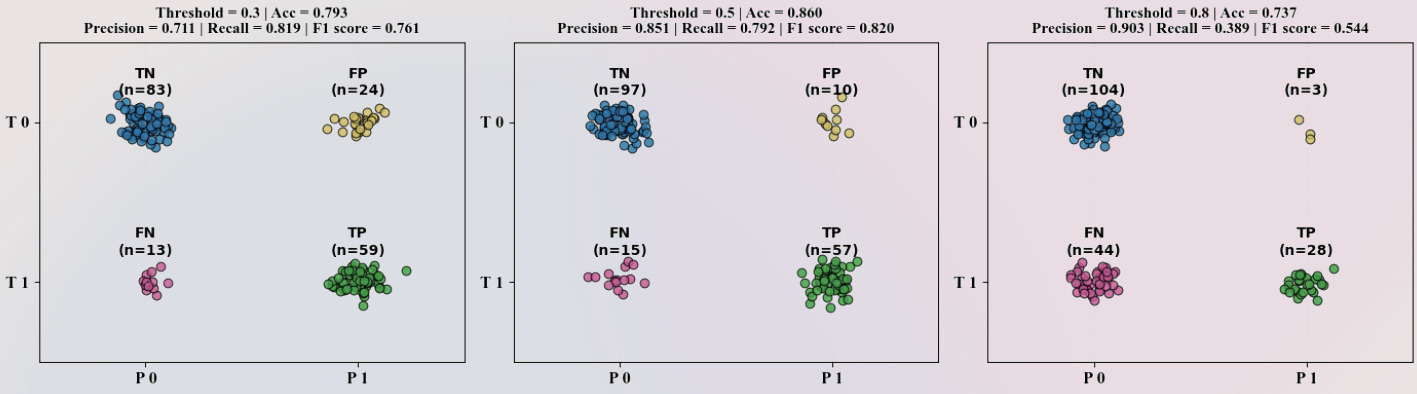
Probability density的集中顯示模型在引入語意特徵後，能將原本分散的樣本投影到更一致的決策區域，反映出關聯結構被更有效的抓取。

Feature × Logit



透過logit空間可以觀察到positive與negative呈現更穩定的可分趨勢。

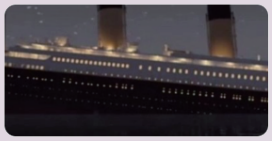
Feature × Confusion matrix



confusion matrix有著明顯的改變，模型針對誤判positive與negative有著顯著的下降，雖然保守但是結果較為穩定。

Titanic - Machine Learning from Disaster

Start here! Predict survival on the Titanic and get familiar with ML basics



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Submissions

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Submission and Description	Public Score
submission.csv Complete · now	0.77511

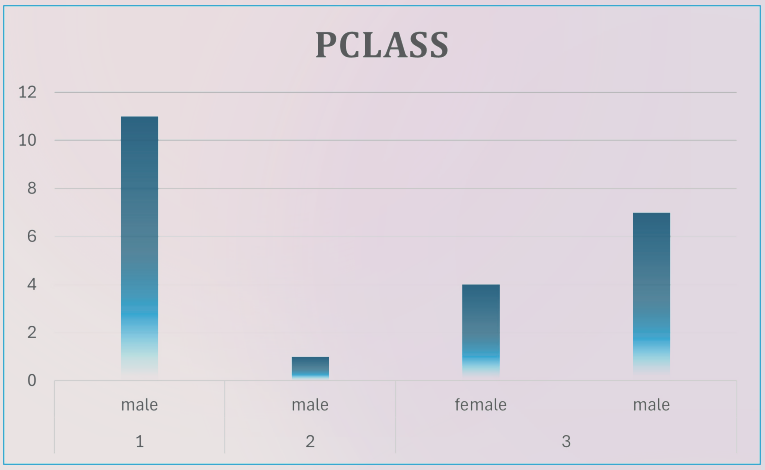
Model architecture

```
class Titanic(nn.Module):
    def __init__(self, input_dim, hidden=16, depth=2, dropout=0.3):
        super().__init__()
        self.depth = depth
        self.dropout = nn.Dropout(dropout)
        self.fc1 = nn.Linear(input_dim, hidden)

        if depth == 2:
            self.fc2 = nn.Linear(hidden, hidden // 2)
            self.fc3 = nn.Linear(hidden // 2, 1)
        else:
            self.fc2 = nn.Linear(hidden, 1)

    def forward(self, x):
        x = F.relu(self.fc1(x))
        x = self.dropout(x)
        if self.depth == 2:
            x = F.relu(self.fc2(x))
            x = self.dropout(x)
            logits = self.fc3(x)
        else:
            logits = self.fc2(x)
        return logits
```

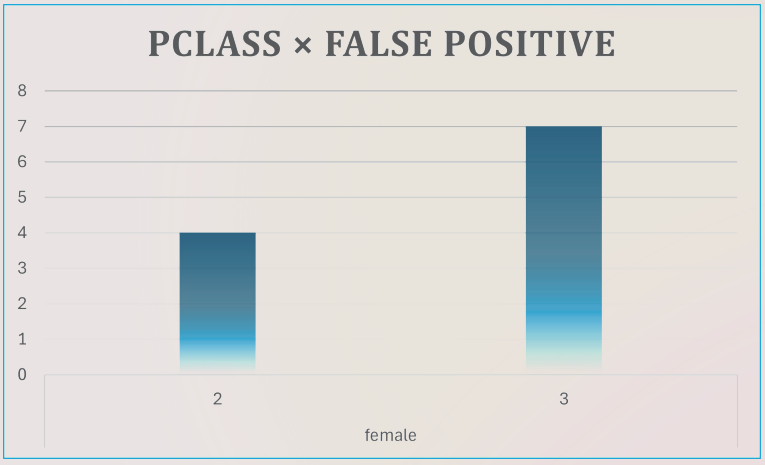
從前置feature engineering的重要性包含到interaction feature的設置與test當中最後使用ensemble測試seed的穩定性。資料結構本身可詮釋上限，以及model architecture選擇的重要。

結果:或許?還有尚未找齊的特徵未納入，嘗試把FN與FP輸出尋找關聯性。

False negative

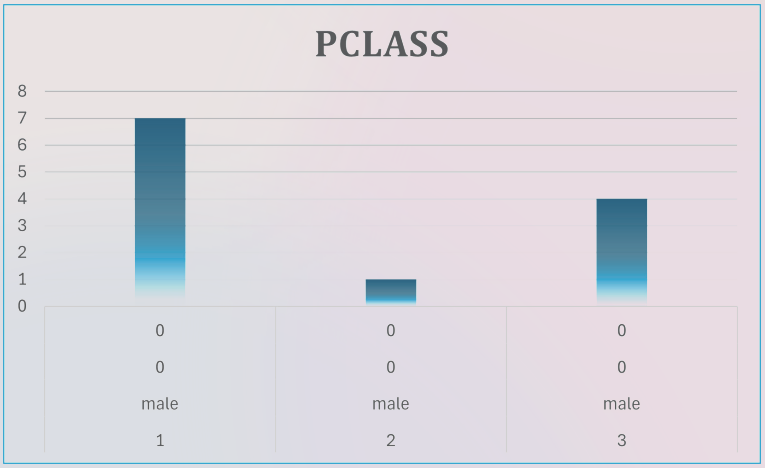


樞紐圖False negative的大部分是男性，且pcalss = 1的佔比非常多，根據我們設定的模型世界觀，資料顯示，也許當中並未與其他人發生組合抑或是Sex特徵過於強，導致模型無法模擬其他交互關係。



檢查False positive觀察，確實Sex特徵具有強烈暗示模型行為。

SibSp × Parch (FN)



篩選出SibSp與Parch的為0的欄位統計，驗證結果，在目前的特徵設計下模型傾向將solo類別視為缺乏可分的訊號樣本，導致預測信心降低（尤其是針對Sex主要特徵）。

Conditional modeling

[Female BEST RESULT]

Threshold : 0.50
Accuracy : 0.873
Precision : 0.882
Recall   : 0.957
F1-score : 0.918

TN: 10 | FP: 6
FN: 2 | TP: 45

[Male BEST RESULT]

Threshold : 0.15
Accuracy : 0.750
Precision : 0.410
Recall   : 0.727
F1-score : 0.525

TN: 71 | FP: 23
FN: 6 | TP: 16

Feature

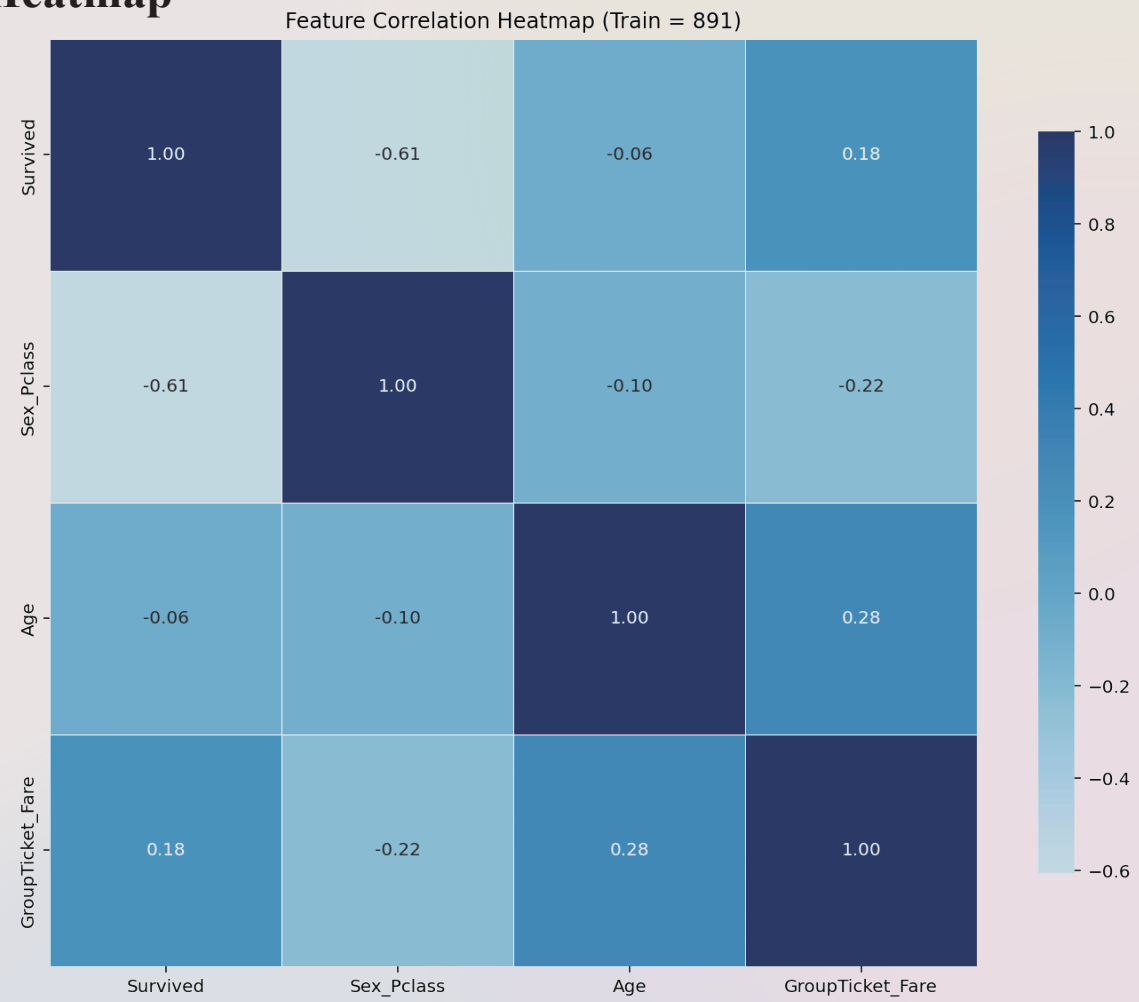
num_columns = ['Age', 'SibSp', 'Parch', 'Fare']

cat_columns = ['Pclass', 'Embarked']

本次表格採用最基本的feature
進行Sex個別測試。

嘗試引入條件訓練，將Sex進行分流檢驗結果，該結果顯示模型針對male判斷有些激進需要依賴調低threshold才能增加recall從目前基礎特徵發現尚不足以達成穩定true positive與negative的判斷，可能需要更具體條件的特徵交互補強。

Heatmap



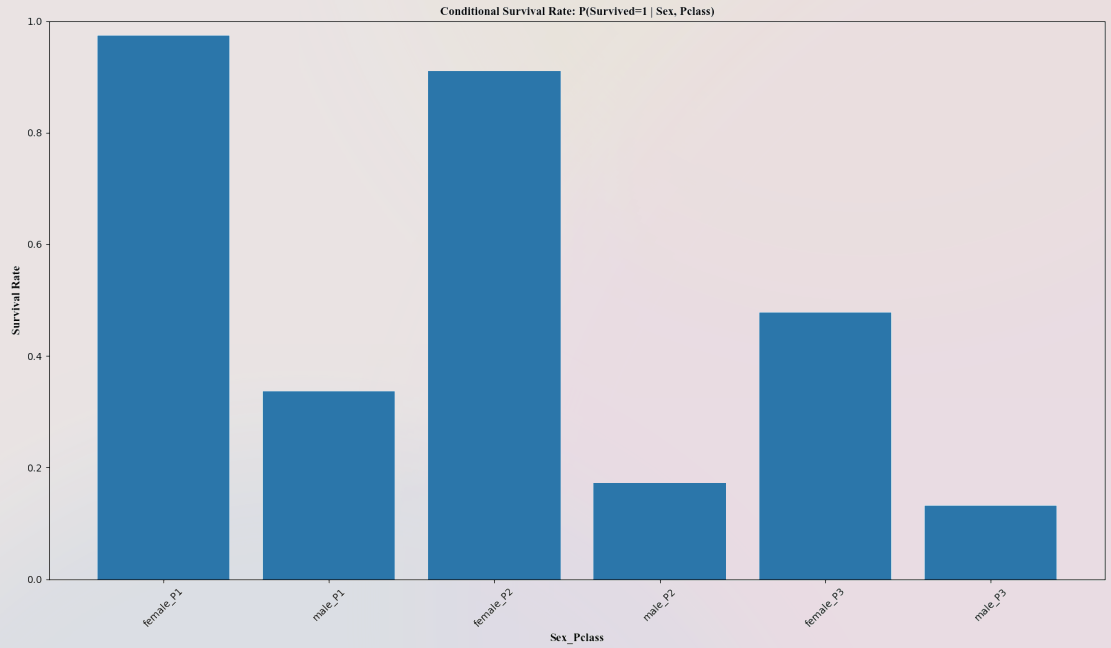
透過heatmap查看feature engineering結構是否存在相互矛盾，目前結果顯示與之設定條件吻合。
主要特徵sex_pclass，輔助特徵groupticket_fare, 次要特徵age。

Cross validation

```
CV ONLY | K=5 | HIDDEN=32 | DEPTH=2 | LR=0.0003 | DROPOUT=0.3

================ Fold 1/5 ================
[VAL @ threshold=0.30] | ACC = 0.7821 | Precision= 0.6923 | Recall= 0.7826 | F1_balance= 0.7347 | TP=54  FP=24  FN=15  TN=86
[VAL @ threshold=0.50] | ACC = 0.8045 | Precision= 0.8036 | Recall= 0.6522 | F1_balance= 0.7200 | TP=45  FP=11  FN=24  TN=99
[VAL @ threshold=0.80] | ACC = 0.7709 | Precision= 0.9667 | Recall= 0.4203 | F1_balance= 0.5859 | TP=29  FP=1  FN=40  TN=109

================ Fold 2/5 ================
[VAL @ threshold=0.30] | ACC = 0.8034 | Precision= 0.7143 | Recall= 0.8088 | F1_balance= 0.7586 | TP=55  FP=22  FN=13  TN=88
[VAL @ threshold=0.50] | ACC = 0.8034 | Precision= 0.7619 | Recall= 0.7059 | F1_balance= 0.7328 | TP=48  FP=15  FN=20  TN=95
[VAL @ threshold=0.80] | ACC = 0.7697 | Precision= 0.9091 | Recall= 0.4412 | F1_balance= 0.5941 | TP=30  FP=3  FN=38  TN=107

================ Fold 3/5 ================
[VAL @ threshold=0.30] | ACC = 0.7584 | Precision= 0.6374 | Recall= 0.8529 | F1_balance= 0.7296 | TP=58  FP=33  FN=10  TN=77
[VAL @ threshold=0.50] | ACC = 0.8483 | Precision= 0.8475 | Recall= 0.7353 | F1_balance= 0.7874 | TP=50  FP=9  FN=18  TN=101
[VAL @ threshold=0.80] | ACC = 0.8202 | Precision= 1.0000 | Recall= 0.5294 | F1_balance= 0.6923 | TP=36  FP=0  FN=32  TN=110

================ Fold 4/5 ================
[VAL @ threshold=0.30] | ACC = 0.7697 | Precision= 0.6709 | Recall= 0.7794 | F1_balance= 0.7211 | TP=53  FP=26  FN=15  TN=84
[VAL @ threshold=0.50] | ACC = 0.7865 | Precision= 0.7778 | Recall= 0.6176 | F1_balance= 0.6885 | TP=42  FP=12  FN=26  TN=98
[VAL @ threshold=0.80] | ACC = 0.6180 | Precision= 0.0000 | Recall= 0.0000 | F1_balance= 0.0000 | TP=0  FP=0  FN=68  TN=110

================ Fold 5/5 ================
[VAL @ threshold=0.30] | ACC = 0.7697 | Precision= 0.6458 | Recall= 0.8986 | F1_balance= 0.7515 | TP=62  FP=34  FN=7  TN=75
[VAL @ threshold=0.50] | ACC = 0.8708 | Precision= 0.8286 | Recall= 0.8406 | F1_balance= 0.8345 | TP=58  FP=12  FN=11  TN=97
[VAL @ threshold=0.80] | ACC = 0.8034 | Precision= 0.9250 | Recall= 0.5362 | F1_balance= 0.6789 | TP=37  FP=3  FN=32  TN=106

================ CV Summary (mean ± std) ================

[t=0.30] ACC 0.7766±0.0171 | P 0.6721±0.0320 | R 0.8245±0.0508 | F1 0.7391±0.0156 || TP~56.4 FP~27.8 FN~12.0 TN~82.0
[t=0.50] ACC 0.8227±0.0353 | P 0.8039±0.0352 | R 0.7103±0.0860 | F1 0.7527±0.0581 || TP~48.6 FP~11.8 FN~19.8 TN~98.0
[t=0.80] ACC 0.7564±0.0804 | P 0.7602±0.4264 | R 0.3854±0.2216 | F1 0.5102±0.2893 || TP~26.4 FP~1.4 FN~42.0 TN~108.4
```

cross validation揭示了在Fold 4資料當中存在大量非典型樣本，導致在threshold = 0.8時產生異常數據。precision, recall, f1 = 0.000 (TP = 0, FP = 0)，模型同樣都對positive無法產生足夠的信心判斷，顯示出標籤與特徵的矛盾。

Conditional Survival Rate



確認原本的sex與pclass這條特徵組合對於survived的資料客觀允許機率，可以看見該組合具備分類性，雖然存在模糊帶，但其可達信心上限仍受樣本數、模糊子群、正則化與模型校準影響。
我所採用的validation loop驗證了在目前feature space與模型族群下，性能達到上限，在反覆的驗證與推翻之後，目前沒有更好的答案，也或許沒有最好的答案，只有合適的答案。