

# Example Scenario: Personalized Health Insurance Recommendations

## User Profile

- **Age:** 35
  - **Location:** Melbourne
  - **Health Needs:** Maternity coverage, no waiting periods.
  - **Budget:** Prefers policies under \$150/month.
  - **Additional Preferences:** Prefers insurers with high customer satisfaction ratings.
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## Step-by-Step Breakdown

### 1. Data Collection

- **User Data:**
  - Age: 35
  - Location: Melbourne (encoded as a categorical feature, e.g., "VIC").
  - Health Needs: Maternity coverage (encoded as a binary feature: 1 for maternity, 0 otherwise).
  - Budget: \$150/month (normalized to a scale of 0–1, e.g., 0.75).
  - Customer Satisfaction Preference: High (encoded as a binary feature: 1 for high, 0 for low).
- **Policy Data:**
  - **Policy X:**
    - Premium: \$120/month (normalized to 0.6).
    - Waiting Period: 0 days for maternity (encoded as 0).
    - Coverage: Maternity, dental, optical.
    - Insurer Rating: 4.5/5 (normalized to 0.9).
  - **Policy Y:**
    - Premium: \$135/month (normalized to 0.675).
    - Waiting Period: 30 days for maternity (encoded as 30).
    - Coverage: Maternity, neonatal care, hospital.
    - Insurer Rating: 4.2/5 (normalized to 0.84).
  - **Policy Z:**
    - Premium: \$110/month (normalized to 0.55).
    - Waiting Period: 0 days for maternity (encoded as 0).
    - Coverage: Maternity, partnered with Royal Women's Hospital.
    - Insurer Rating: 4.7/5 (normalized to 0.94).
- **Interaction Data:**

- Historical data showing that users with similar profiles (e.g., age 30–40, maternity needs) often prefer policies with no waiting periods and high insurer ratings.
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## 2. Model Input

The user's features are preprocessed and fed into the **User Tower** of the TFRS model:

```
python
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user_input = {
    "age": 0.35, # Normalized (35 / 100)
    "location": "VIC", # Categorical (Victoria)
    "maternity_coverage": 1, # Binary (1 = needed)
    "budget": 0.75, # Normalized ($150/month)
    "insurer_rating_preference": 1 # Binary (1 = high rating preferred)
}
```

The **Policy Tower** processes the policy features:

```
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policy_dataset = [
    {
        "premium": 0.6,
        "waiting_period": 0,
        "coverage": ["maternity", "dental", "optical"],
        "insurer_rating": 0.9
    },
    {
        "premium": 0.675,
        "waiting_period": 30,
        "coverage": ["maternity", "neonatal", "hospital"],
        "insurer_rating": 0.84
    },
    {
        "premium": 0.55,
        "waiting_period": 0,
        "coverage": ["maternity", "hospital_partnership"],
        "insurer_rating": 0.94
    }
]
```

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## 3. Model Inference

The TFRS model computes embeddings for the user and policies, then calculates similarity scores:

```
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```

```
# User embedding
user_embedding = model.user_model(user_input)

# Policy embeddings
policy_embeddings = model.policy_model(policy_dataset)

# Similarity scores (dot product)
scores = tf.matmul(user_embedding, policy_embeddings, transpose_b=True)
```

The scores might look like this:

- Policy X: 0.92
  - Policy Z: 0.89
  - Policy Y: 0.75
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## 4. Top-K Recommendations

The model retrieves the top-2 policies based on similarity scores:

```
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top_k_indices = tf.math.top_k(scores, k=2).indices.numpy()
recommended_policies = [policy_dataset[i] for i in top_k_indices]
```

### Output:

1. **Policy X:**
    - Premium: \$120/month
    - Waiting Period: 0 days for maternity
    - Coverage: Maternity, dental, optical
    - Insurer Rating: 4.5/5
  2. **Policy Z:**
    - Premium: \$110/month
    - Waiting Period: 0 days for maternity
    - Coverage: Maternity, partnered with Royal Women's Hospital
    - Insurer Rating: 4.7/5
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## 5. Explanation for Recommendations

The platform provides explanations for why these policies were recommended:

- **Policy X:**
  - "Recommended because it has no waiting period for maternity and fits your budget."
- **Policy Z:**

- "Recommended because it partners with Royal Women's Hospital and has a high insurer rating."
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## 6. User Interaction

The user can:

- Click on a policy to view detailed coverage and exclusions.
  - Adjust filters (e.g., increase budget to \$160/month) to see updated recommendations.
  - Compare policies side-by-side.
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## Technical Implementation Details

### Model Training

- **Loss Function:**  
Use a retrieval task with factorized top-K metrics to optimize for accurate policy recommendations.

```
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```

```
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```

```
task = tfrs.tasks.Retrieval(  
    metrics=tfmetrics.FactorizedTopK(  
        candidates=policy_dataset.batch(128).map(policy_model)  
    )  
)
```

- **Training Data:**  
Use historical user-policy interactions (e.g., clicks, purchases) to train the model.  
Example:

```
python
```

```
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```

```
train_data = tf.data.Dataset.from_tensor_slices({  
    "user_features": user_data,  
    "policy_features": policy_data,  
    "interaction": interaction_labels # 1 (clicked/purchased) or 0 (ignored)  
})
```

### Deployment

- **API Endpoint:**

Deploy the model using **TensorFlow Serving** or **FastAPI** to serve recommendations in real time.

Example API call:

json

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```
POST /recommendations
{
  "user_id": "123",
  "features": {
    "age": 35,
    "location": "VIC",
    "maternity_coverage": 1,
    "budget": 150,
    "insurer_rating_preference": 1
  }
}
```

- **Response:**

json

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```
{
  "recommended_policies": [
    {
      "policy_name": "Policy X",
      "premium": 120,
      "waiting_period": 0,
      "coverage": ["maternity", "dental", "optical"],
      "insurer_rating": 4.5
    },
    {
      "policy_name": "Policy Z",
      "premium": 110,
      "waiting_period": 0,
      "coverage": ["maternity", "hospital_partnership"],
      "insurer_rating": 4.7
    }
  ]
}
```

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## Business Impact

- **Increased Conversions:** Personalized recommendations lead to higher engagement and purchase rates.
- **Improved User Satisfaction:** Users find policies tailored to their needs, reducing decision fatigue.

- **Competitive Advantage:** Differentiates the platform from competitors using rule-based or non-AI systems.
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This detailed example demonstrates how TensorFlow Recommenders can be used to deliver **personalized, data-driven health insurance recommendations** in the Australian market.