# Phase 2

## SYSTEMS FOR MACHINE LEARNING

EE 599

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#### 1 LLaMA2 Model Inference

The KV caching only happens in the inference phase, so we need to modify all forward propagation in model.py.

In class Attention(nn.Module), we removed all computations about  $self.cache_k$  and  $self.cache_v$ , because this two variables selected specific keys and values to calculate the attention map. We replaced them with the original xk and xv.

```
lass Attention(nn.Module):
   """Multi-head attention module."""
   def __init__(self, args: ModelArgs):
      Args:
          args (ModelArgs): Model configuration parameters.
       Attributes:
          n_kv_heads (int): Number of key and value heads.
          n_local_heads (int): Number of local query heads.
          n_local_kv_heads (int): Number of local key and value heads.
          n_rep (int): Number of repetitions for local heads.
          head_dim (int): Dimension size of each attention head.
          wq (ColumnParallelLinear): Linear transformation for queries.
          wk (ColumnParallelLinear): Linear transformation for keys.
          wv (ColumnParallelLinear): Linear transformation for values.
          wo (RowParallelLinear): Linear transformation for output.
          cache_k (torch.Tensor): Cached keys for attention.
       super().__init__()
       self.n_kv_heads = args.n_heads if args.n_kv_heads is None else args.n_kv_heads
       self.n_local_heads = args.n_heads
       self.n_local_kv_heads = self.n_kv_heads
       self.n_rep = self.n_local_heads // self.n_local_kv_heads
       self.head_dim = args.dim // args.n_heads
       self.wq = nn.Linear(args.dim, args.n_heads * self.head_dim, bias=False)
       self.wk = nn.Linear(args.dim, self.n_kv_heads * self.head_dim, bias=False)
       self.wv = nn.Linear(args.dim, self.n_kv_heads * self.head_dim, bias=False)
       self.wo = nn.Linear(args.n_heads * self.head_dim, args.dim, bias=False)
```

```
def forward(
   x: torch.Tensor,
    freqs_cis: torch.Tensor,
   mask: Optional[torch.Tensor],
   Forward pass of the attention module.
   Args:
       start_pos (int): Starting position for caching.
       torch. Tensor: Output tensor after attention.
   bsz, seqlen, _ = x.shape
   xq, xk, xv = self.wq(x), self.wk(x), self.wv(x)
   xq = xq.view(bsz, seqlen, self.n_local_heads, self.head_dim)
   xk = xk.view(bsz, seqlen, self.n_local_kv_heads, self.head_dim)
   xv = xv.view(bsz, seqlen, self.n_local_kv_heads, self.head_dim)
   xq, xk = apply_rotary_emb(xq, xk, freqs_cis=freqs_cis)
   keys = repeat_kv(xk, self.n_rep) # (bs, cache_len + seqlen, n_local_heads, head_dim)
   values = repeat_kv(xv, self.n_rep) # (bs, cache_len + seqlen, n_local_heads, head dim)
   xq = xq.transpose(1, 2) # (bs, n_local_heads, seqlen, head_dim)
   keys = keys.transpose(1, 2) # (bs, n_local_heads, cache_len + seqlen, head_dim)
   values = values.transpose(1, 2) # (bs, n_local_heads, cache_len + seqlen, head_dim)
   scores = torch.matmul(xq, keys.transpose(2, 3)) / math.sqrt(self.head_dim)
   if mask is not None:
      scores = scores + mask # (bs, n_local_heads, seqlen, cache_len + seqlen)
   scores = F.softmax(scores.float(), dim=-1).type_as(xq)
   output = torch.matmul(scores, values) # (bs, n_local_heads, seqlen, head_dim)
   output = output.transpose(1, 2).contiguous().view(bsz, seqlen, -1)
   return self.wo(output)
```

In the last part, class Llama(Generation), we modified the mask and reserved all elements so that the attention map remains rectangular.

```
def __init__(self, params: ModelArgs):
     self.freqs_cis = precompute_freqs_cis(
         # Note that self.params.max_seq_len is multiplied by 2 because the token limit for the Llama 2 gener
# Adding this multiplier instead of using 4096 directly allows for dynamism of token lengths while t
         self.params.dim // self.params.n_heads, self.params.max_seq_len * 2
def forward(self, tokens: torch.Tensor, start_pos: int):
     _bsz, seqlen = tokens.shape
    h = self.tok_embeddings(tokens)
    self.freqs_cis = self.freqs_cis.to(h.device)
freqs_cis = self.freqs_cis[start_pos : start_pos + seqlen]
    mask = None
    if seglen > 1:
         mask = torch.full(
             (seqlen, seqlen), float("-inf"), device=tokens.device
         mask = torch.triu(mask, diagonal=1)
         mask = mask.unsqueeze(0).unsqueeze(1) # (1, 1, seqlen, seqlen)
     for layer in self.layers:
         h = layer(h, start_pos, freqs_cis, mask)
    h = self.norm(h)
    output = self.output(h).float()
     return output
```

The original output is shown as below. It can be found that all prompts output meaningful context.

```
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```

The output that removes KV Caching is shown as below. The output becomes meaningless gibberish. It is speculated that the current model will consider future inputs, making the output logic confusing.